

Functional State Evaluation System with Distributed Intellect for Elderly and Disabled Persons

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Abstract. The main aim of this paper is to develop the system for recording and analysis of human vital signals. The decision-making algorithms are based on the complex system theory and distributed intellect and convolution of Mealy and Moore automata. In case of dangerous situation, a smart phone can send the alarm signal and analysis results to a physician's server. The exceptional feature of the developed monitoring system is the synchronous analysis of multiple processes and integrated assessment of person's functional state adaptation for user requirements at the individual level.

Keywords: monitoring system, convolution of automata, signal analysis, complex systems

I. INTRODUCTION

Technological advances in wireless networking, microelectronics and sensors, as well as in medical information technologies allow us to change the way health care services are deployed and delivered [1]. Focus on prevention and early detection of disease or optimal maintenance of chronic diseases promise to improve the existing healthcare systems that are mostly structured and optimized for reacting to crisis and managing illness [2-7]. Studies in this field show that during obsolescence processes the complexity of functional state decreases, and herewith the person's potential of adaptation decreases, too [8]. Therefore, the development and adaptation of new methods for evaluation of human body complexity has been one of the aims of the present research. It is likely that the early assessment of complexity changes will allow starting the earlier usage of preventive means with intention to preclude the manifestation of various disorders and dangerous situations in the human organism. Another possibility for taking the preventive measures can be the estimation of values of individual physical activity necessary for every person with the aim to avoid the opposite effect – having too little or too much physical activity may have the negative impact on a person's health.

These prospective methods and the hardware designed for safety of elderly people at home represent a new diagnostic technology, and the development of this technology has been one of the goals of ITEA2 08018 GUARANTEE [9] and EUREKA E14452 EDFAS [10] projects.

II. THE ARCHITECTURE OF HUMAN MONITORING AND ANALYSIS SYSTEM

The developed system architecture consists of three levels: the first one encompasses a mobile patient recorder (MPR), the second level is the mobile phone, and the third level

encompasses the network of a remote server for medical experts. The MPR consists of intelligent sensors for simultaneous recording and wireless transmission of three ECG leads, three accelerometer signals (ACS), one plethysmogram (PPG) and oxygen saturation (SpO₂) channel. The personal server is the Internet-enabled digital assistant (PDA) with the real-time data analysis software. The remote server is the network with personal computers (PC), off-line data analysis software and data base.

The architecture of human monitoring and analysis system is presented in Fig. 1.

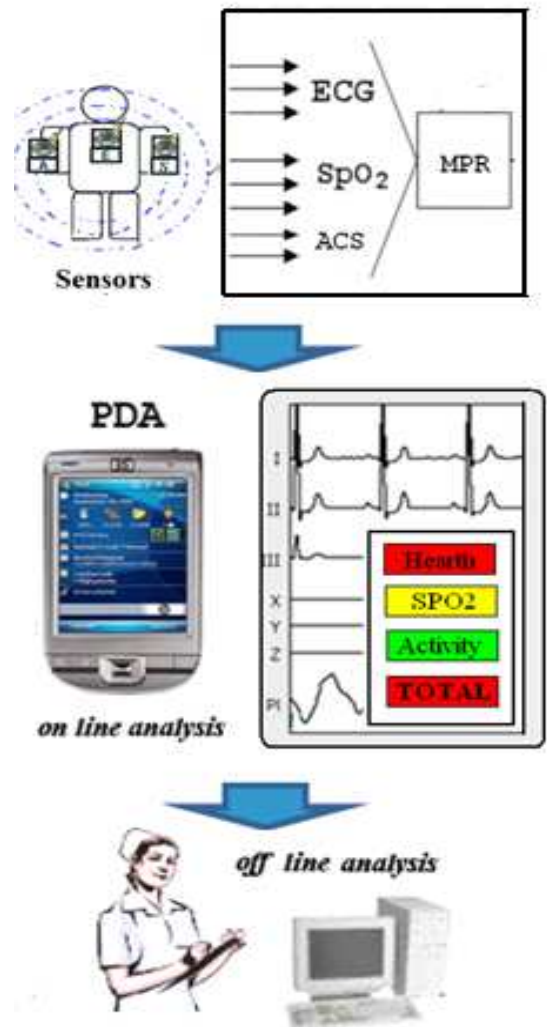


Fig. 1. Architecture of the system

The functioning of MPR, PDA and physician's PC monitoring data analysis is illustrated in Fig. 2. The decision-

making process about the person's functional state is performed according to the principles based on the methodology of distributed intellect.

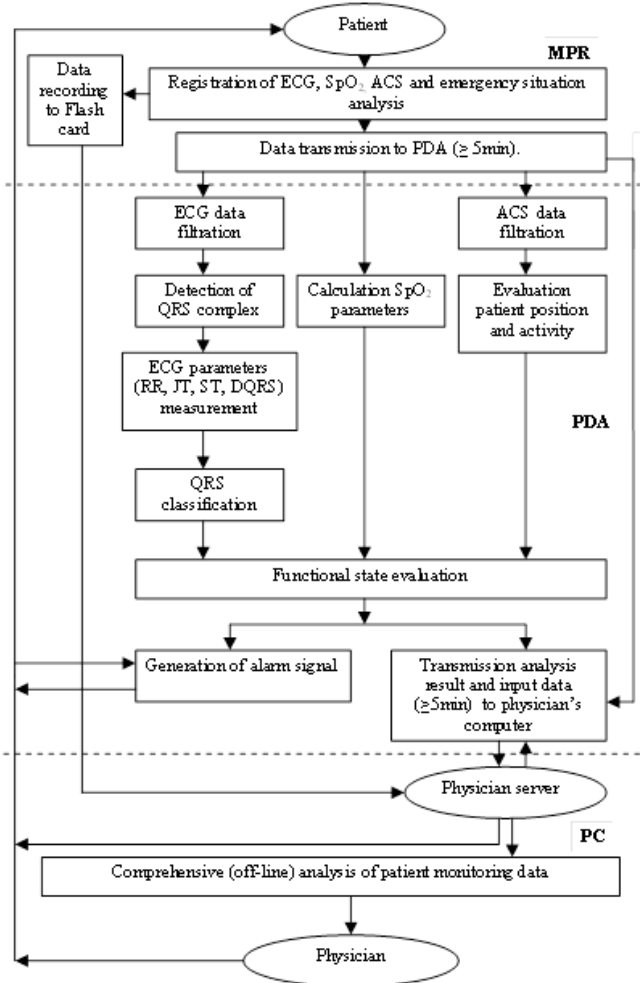


Fig. 2. Functional diagram

First of all, the above-mentioned on-line analysis of processes is performed, and subject to its results (dangerous status) a more detailed analysis of person's functional state is performed off-line by using multi-stage non-linear analysis methods and evaluation of complexity changes as a measure of the human organism status.

The structural diagram of the developed mobile patient recorder is presented in Fig. 3. Low-power three-channel ECG amplifier is built using INA333 Micro-Power (50mKA), zero-drift, rail-to-rail output instrumentation amplifier produced by Texas Instruments. This instrumentation amplifier has RFI filtered inputs with very high input impedance, which typically is about 100GΩ. Baseline reference is regulated from a microcontroller by using a cheap 4-channel digital-to-analog converter DAC104S085. Analog signals are sampled by 4-channel, ultra low noise, 24-bit sigma-delta analog-to-digital converter (ADC) AD7193 from Analog Devices. Main microcontroller is MSP430F5438, which at regular time intervals (500 samples/second), samples incoming signals and preprocesses the acquired signals. Photoplethysmography signal is acquired using PureSAT 8000R reflectance sensor

and NONIN OEM III module for signal preprocessing. Biomechanical data, acceleration in X, Y, Z axes, are measured by digital accelerometer ADXL346 (Analog Devices Inc.). Accelerometer is mounted inside the logger unit and has programmable sensitivity ranges from 2g up to 16g, thus allowing a wide range of movement to be recorded without disruption.

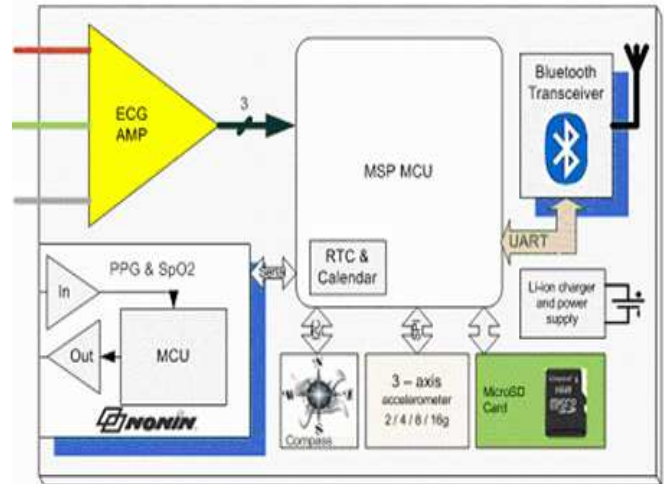


Fig. 3. Structural diagram

As of now, the acceleration sensitivity range is selected manually, but it should be possible to select it automatically with the intelligent preprocessing inside firmware. Gathered data is being accumulated into internal buffers while its size achieves page size in MicroSD card storage. Then the data buffers are transferred to MicroSD card file system and / or transferred by Bluetooth wireless link to PDA or PC for the analysis. MicroSD card capacity is 1 GB; however, any standard card with FAT32 file system is suitable.



Fig. 4. Photo of MPR

Bluetooth module is BlueMod+P25/G2 class 2, Bluetooth v2.0+EDR made by Stollmann E+V GmbH. This module is able to communicate via Health Device Profile (HDP); thus, it fits medical device category. Powerful and lightweight Li-ion

battery allows long time recording; the minimum expected time for real time data acquisition is 24 hours. Charging of the battery is accomplished by using MCP73832. It is a simple Li-ion battery charger, which allows recharging of the battery by plugging device to a standard USB port or a wide range of mobile chargers with MiniUSB connector. The photo of MPR is presented in Fig. 4.

III. THE ON-LINE ANALYSIS ALGORITHMS

Biomechanical and physiological signal acquiring device allows recording three ECG leads, three accelerometers and two oxygen saturation channels simultaneously (Fig. 5).

The ECG analysis algorithm includes the identification of complexes, parameter measurement and classification of ECG complexes. The algorithm of ECG analysis is intended for the analysis of five-minute long record in three-channel ECG.

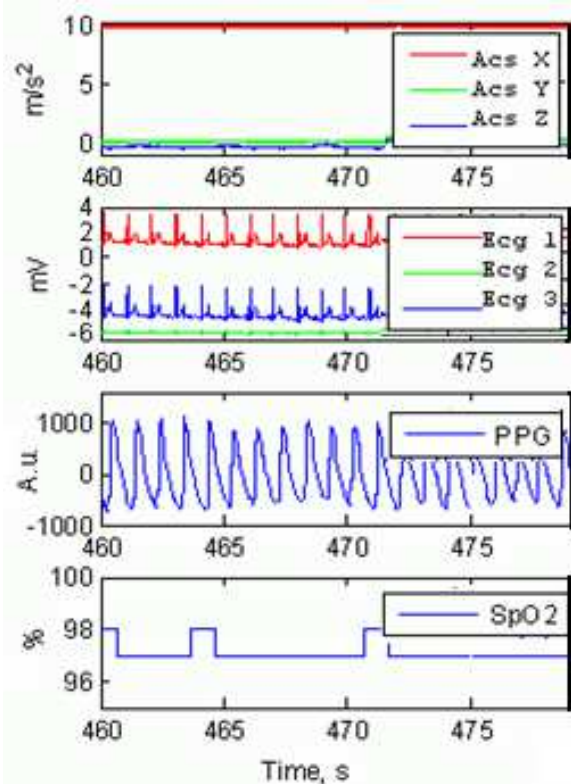


Fig. 5. Example of the recorded data

The first aim of the ECG complex classification is the identification of P-QRS-T complexes. Requirements for long ECG recording recognition algorithms: adaptation to a wide QRS complex amplitude change, adaptation to a wide variation of RR intervals, adaptation to various signal quality, elimination of artifacts.

In order to avoid the wide QRS complex amplitude and RR interval variations, we have applied the QRS wave detection algorithm to the ECG record of ten-second duration. First, noise levels in the three channels have been defined. The channel, whose noise level has not exceeded the noise level of the threshold of U1, has been included in the authentication process without filtering. The channel, whose noise level has exceeded the threshold of U1, but has been below the

threshold of U2 – has been filtered by a digital filter. The channel, whose noise level has exceeded the threshold of U2 – has been excluded from the subsequent ECG elements of the authentication process. Next, the detection procedure of QRS wave point-by-point to entire ECG record has been applied to determine the beginning and end of wave strips. The recognition method of the ECG waves and complexes (P, QRS, ST-T) is based on a scalar function $T(t)$, and consists of a vector signal $W = Y_k(t)$, where k – the number of simultaneous ECG channels. The transformation $T(t)$ is multiphase function near zero in the ECG isoelectric line and significantly different from zero in parts of the ECG complexes. The function $T(t)$ has been normalized according to the amplitude.

Heart rate (HR):				
HFi;	i = 1	2	3	4
[bpm]	0-40	40-100	100-140	140 and more
HR ⁿ i;	i = 1	2	3	
	the same	higher	less	
ΔHR	± 25%	> 25%	< 25%	
QRS complex duration (DQRS):				
DQRSi;	i=1	2	3	
[ms]	70-100	100-120	120-140	
DQRS ⁿ i;	i=1	2	3	
	the same	longer	shorter	
ΔDQRS	± 20%	> 20%	< 20%	
ST segment amplitude in any of three ECG leads:				
STi;	i=1	2		
	0-0,1mV	> 0,1mV		
Δ/STi ⁿ ;	i=1	2	3	
	the same	bigger	less	
When Δ/STi ⁿ ;	0-0,1mV	> 0,1mV	< 0,1mV	

Fig. 6. Rules for ECG parameter evaluation

For QRS wave classification algorithm, the groups of morphologically similar complexes have been constructed after QRS complexes and T wave identification. The first complex has become a benchmark in the first group. Next complex has been compared with the benchmark of the first group. Two complexes have been stacked on each other to compare their R wave peaks. The vector of the first group benchmark has been formed as $E(1) = (e(1), e(2), \dots, e(L))$. Then the m -th complex has been compared with the first group by calculating the distance ρ_1^m between the m -complex and a representative complex from the first group. If $\rho_1^m \leq \rho^s$ (ρ^s - similarity threshold value), the benchmark is assigned to this group and it is recalculated for group $E(1)$. If $\rho_1^m > \rho^s$, the complex is compared to benchmarks in other groups (if they exist), or becomes a benchmark in the new group. All

recognized complexes are classified into five classes: N – dominant, i.e., complexes, which are not present in the S , V , F or Q -classes; S – supraventricular complexes; V – ventricular complexes; F – fusion, i.e., merge of ventricular and dominant complexes; Q – unclassified, i.e., stimulant – stimulant merges with dominant complexes or unclassified complexes.

Oxygen saturation (SpO ₂) in %				
SpO ₂ i;	i=1	2	3	4
SpO ₂ i	100-96	95-90	90-85	85 and less
SpO ₂ "	the same	higher	less	
ΔSpO ₂ i	± 25%	> 25%	< 25%	
Motion activity processes (ACS):				
Body state				
Acsi;	i=1	2	3	
	supine	upright	urgent alarm	
Acs"i;	i=1	2	3	
	the same	stands up	lie-down	
Evaluation of movement (M):				
Mi;	i=1	2	3	
	stationary	small	high	
Mi"i;	i=1	2	3	
	the same	higher	less	

Fig. 7. Criteria for evaluation of oxygen saturation and motion activity data

The criteria of the ECG parameters for the patient's functional state evaluation are presented in Fig. 6; the criteria for evaluation of oxygen saturation and motion activity data are presented in Fig. 7. It should be mentioned that limits of parameters can be chosen individually regarding normal personal parameter values.

IV. DECISION-MAKING METHODS

Finally, the monitoring system makes a main decision about the patient's state changes from the calculated parameters by using convolution of Moore and Mealy automata [11-12]. According to the received analysis results, the software forms warning signals (green, yellow, red) to a patient. In case of dangerous situation for a patient, the software sends the results of the analysis to a physician.

The complex calculations should be formalized or automated. For this purpose, the special derivative – the convolution of Moore and Mealy automata can be used (Fig. 8). In this derivative, the output signals of one automaton are input signals to another automaton. Output information (a result of work of formal automata) becomes the information collection of these automata, i.e., the time series evolution of the states of automata is recorded and investigated. Such convolution of automata has the advantage: the investigated dynamical systems levels can be encoded by automata. This can be done by adding one automata convolution into another.

Moreover, the time moments can be hierarchically ordered in these automata, while an adequate model of the investigation system is being created.

The automated health assessment subsystem will implement the proposed algorithm for assessing the complexity of ECG dynamics – He ranking calculation algorithm of H rank, a broader description and theoretical assumptions can be found in [10].

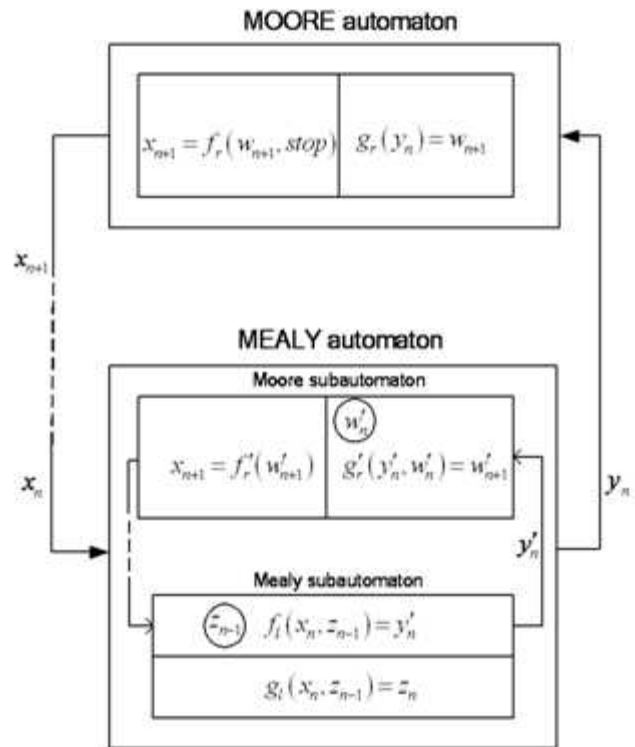


Fig. 8. Convolution of the automation

The diagnostics of disease process (the interaction of a doctor, different instrumentation and patient) is interpreted as the operation of convolution of automata. The states of Moore automaton w describe the experience of the disease diagnosis, the compendium of various health parameters of patients. The states of Mealy automaton z describe the survey of patient's health status (the survey of his physiological parameter measurement). The output signals of Mealy automaton – the input signals of Moore automaton y describe the evaluation of the health parameters of patient's state during the diagnostic investigation. The output signals of Moore automaton – the input signals of Mealy automaton x describe instructions sent to Mealy automaton.

Moore automaton decides on the threatening nature of the situation and the degree of the action – the warning of a patient, call to a doctor or ambulance, further tracking. However, Moore automaton (System Administrator) makes a decision, it performs further monitoring.

Thus, the integral algorithm of the body state assessment is obtained. While performing the automated analysis and implementing the monitoring of the physiological processes, the special task for software – quickly and adequately respond to a person's functional status changes in real time – is required. Such a model should be evaluated in

the parallel processes – ECG, respiratory rate, and movement – and the findings of the analysis ratio.

The result of implementing the convolution of automata is the complexity profile graph, meaning the body's state during the exercise of variable load (see Figure 9).

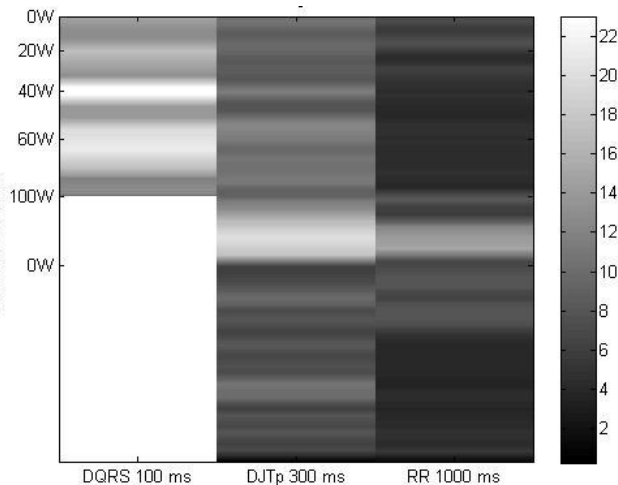


Fig. 9. Complexity profile

The complexity is measured using a colour code – the higher the complexity, the brighter the colour is, and vice versa in the chart (RR parts mean the total body complexity, DJTp – the heart complexity, DQRS parts – the complexity of the inner heart processes). The model of convolution of Moore and Mealy automata has been chosen so that it is possible to add new components (subautomata, states, functions), which allow obtaining a more detailed description of the information flow and adapting the model for a specific task. For example, if you need to use one more ECG signal parameter, the complex output function of Mealy subautomaton can be added to another component. The available data may also be analysed by an additional mathematical method, introducing the parallel Moore subautomaton into convolution, etc. Moreover, the convolution of automata allows you to track a feedback.

The on-line analysis algorithms have been developed by Microsoft Visual Studio 2008 Professional Edition. In PDA, the main operating system has been Windows Mobile 6.5. The experimental program has been developed for the algorithm verification and correction in Windows 32-bit environment using the Borland compiler; the evaluation of complexity has been performed using the Matlab software.

V. RESULTS AND CONCLUSIONS

The research presented in the paper reflects the developed hardware and software of monitoring system, as well as the proposed data analysis with decision-making algorithms.

The new feature of the developed human data monitoring system is the ability to analyse multiple processes in some functional connections of the investigated persons. The integrated assessment of the person's functional state is adapted for user requirements at the individual level. If a patient is in danger or needs external help, the data can be sent

to the medical service center. The mobile patient recorder and data analysis algorithms have been tested on 30 elderly and disabled volunteers without obvious cardiac diseases. The rate of false positive cases of alarm generation was 9 percent and false negative – 3 percent.

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Ļūdas Gargasas, Vidmants Jurkonis, Liepa Bikulciene, Aušra Žvironiene, Saulius Daukanta. Funkcionālā stāvokļa novērtēšanas sistēma ar dalīto intelektu vecu cilvēku un invalīdu aprūpei

Mūsdienu sasniegumi sensoru tehnoloģijās, mikroshēmtehnikā, bezvadu tīklos un medicīnas inženierijā ļauj uzlabot pacienta aprūpes iespējas. Profilakse un savlaicīga saslimstības noteikšana, kā arī optimāla atveseļošana pie hroniskas pacienta saslimšanas papildina šo kopēju aprūpes pieeju, kas ir strukturēta un optimizēta lai spētu operatīvi reaģēt pie straujas pacienta veselības pasliktināšanās vai pat pie krīzes situācijas. Savlaicīgi veikta diagnostika un novērtējumi ļauj uzsākt atveseļošanas procesu un izslēgt jaunu slimību parādīšanos.

Darba galvenais mērķis ir izstrādāt pilnībā funkcionējošu sistēmu, kas spēj noteikt un analizēt pacienta biometrisku informāciju (signālus). Izstrādātās sistēmas arhitektūra sastāv no trim komponentēm: mobils pacienta datu ieraksta modulis, mobilais telefons un tīkls attālinātai piekļuvei pie servera, datu saglabāšanai un turpmākai apstrādei. Datu ieraksta modulis sastāv no inteliģentiem uztvērējiem, kas vienlaicīgi spēj ierakstīt un nosūtīt pa bezvadu saiti trīs parametrus: elektrokardiogramma, akselometriskie signāli un informācija par skābekļa daudzumu. Mobilajam telefonam ir programmatūra, kas nodrošina datu analīzi reālā laikā. Attālinātais serveris (personālais dators) kalpo kā autonomās analīzes un datu saglabāšanas centrs.

Lēmuma pieņemšanas algoritms balstās uz sarežģītu sistēmu teorijas, sadalītā intelekta un Mili/Mūra automātiem. Pacienta veselības pasliktināšanās gadījumā viedtālrunis spēj nosūtīt ārstējošam ārstam trauksmes signālu un analīzes datus. Sistēmas novitāte ir izstrādātais vairāku procesu sinhronās analīzes modulis un kompleksais veselības novērtējums.

Sistēmas testos piedalījās 30 pacientu, kam nav izteiktas kardiovaskulāras saslimstības. Sistēmas testos 9% gadījumu tika izdots nepaties trauksmes signāls pie pozitīva lēmuma un 3% pie negatīva lēmuma.

Людас Гаргасас, Видмантас Юрконис, Лиeпа Бикулчeнe, Аушра Жвиронeнe, Саулюс Даукантас. Система оценки функционального состояния с распределенным интеллектом для ухода за престарелыми людьми и инвалидами

Технологические достижения в области беспроводных сетей, микроэлектроники и датчиков а также в медицинских информационных технологий позволяют нам изменить возможности оказания услуг здравоохранения. Профилактика и раннее выявление заболеваний или оптимальное поддержание при хронических заболеваниях обещают дополнить существующую систему здравоохранения, которая, в основном, нацелена и оптимизирована, чтобы можно было бы оперативно реагировать на кризис и течение болезни. Вполне вероятно, что ранние оценки сложности изменения позволят раньше начать использовать профилактические средства с намерением исключить проявление различных заболеваний и опасных ситуаций в организме человека.

Основной целью данной работы была разработка системы учета и анализа человеческих жизненно важных сигналов. Архитектура разработанной системы состоит из трех уровней: первый - мобильный рекордер данных пациента, второй - мобильной телефон, а третий - сеть удаленного сервера медицинских специалистов. Рекордер состоит из интеллектуальных датчиков для одновременной записи и беспроводной передачи трех отведений ЭКГ, трех сигналов акселерометра, одного сигнала плетизмограммы и насыщения кислородом. Мобильный телефон имеет программное обеспечение анализа данных, работающий в реальном времени. Удаленный сервер (персональный компьютер) служит как средство для автономного анализа данных и базы данных.

Алгоритмы принятия решений разработаны на основе теории сложных систем, распределенного интеллекта и автоматов Мура и Милия. В случае возникновения опасной ситуации смартфон может послать сигнал тревоги и данные для анализа результатов в сервер врача. Исключительной особенностью разработанной системы мониторинга является синхронный анализ нескольких процессов и комплексная оценка адаптации функционального состояния человека для пользовательских требований в индивидуальном уровне.

Система протестирована на 30 волонтерах престарелых и инвалидов без выраженных кардиологических заболеваний. Оценка ложно-положительных случаев сигнала тревоги составила 9 процентов и 3 процента – ложно-отрицательных.