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Big Data and real-time examination of patients with atrial fibrillation

Snitser Anatoly Arnoldovich

1. Head of the Department of Anesthesiology-Resuscitation with intensive care ward No 2 of the State Autonomous Health Care Institution "N. A. Semashko Republican Clinical Hospital". ORCID: 0000-0001-5771-9161.

Zakharyan Elena Arkadyevna

2. PhD in Medicine, Associate Professor of the Department of Internal Medicine No. 1 of the S. I. Georgievsky Medical Academy of the Federal State Autonomous Educational Institution of Higher Education "V. I. Vernadsky Crimean Federal University". ORCID: 0000-0002-7384-9705.

Shvets Yuri Yurievich

3. PhD in Law, Associate Professor. V. A. Trapeznikov Institute of Management Problems of the Russian Academy of Sciences. Financial University under the Government of the Russian Federation.

Klyueva Darya Vladimirovna

4. student of the First Medical Faculty of the S. I. Georgievsky Medical Academy of the Federal State Autonomous Educational Institution of Higher Education "V. I. Vernadsky Crimean Federal University". Contact information: kliuewa.dasha2012@yandex.ua , ORCID: 0000-0002-4023-2979.

Molchanenko Violetta Andreyevna

5. student of the First Medical Faculty of the S. I. Georgievsky Medical Academy of the Federal State Autonomous Educational Institution of Higher Education "V. I. Vernadsky Crimean Federal University". Contact information: molchanenko96@mail.ru, ORCID: 0000-0003-2661-6236.

Abstract

The capacity and throughput of medical centers is often insufficient to monitor patients with cardiovascular insufficiency. Modern mobile ECG systems, digital technologies, and intellectualization help in such tasks by automatically processing and analyzing (without additional resources) the patient's condition for any place, channel, or time. Big Data, Data Mining allow us to explore hidden connections in a variety of medical data, giving an opportunity to analyze data with a volume several orders of magnitude higher. In the article, based on the methods and principles of system analysis, statistical and mathematical analysis, the evolutionary potential of Big Data is analyzed, the real-time examination of patients with atrial fibrillation and plethysmogram curves is considered, the statistical intelligent analysis of plethysmogram wave peaks is implemented with the use of a defibrillator-monitor, the Statistica 10.0 package.

Keywords: Big Data, examination, fibrillation, plethysmogram.

Introduction

The concept of "ECG autotranslation", with the help of ECG recording equipment, frequency modulation and signal transmission to the "receiver" was positioned as instrumental for outpatient verification of the patient's condition according to ECG data. Analogs were used in various countries due to their characteristics, in particular, a simplified approach to recording leads, the ease of registration, the feasibility of telemedicine screening solutions for ECG [1], the presence of feedback [2], the possibility of implantation of ECS.

There are also certain "disadvantages" - the number of patients in the observation flow that is limited by the data infrastructure (telephone one, as a rule), the weakness of interactive connections with the center's patients, automatic (especially intelligent) data processing, the capacity of the center's bandwidth, etc.

Only the modern development of individual (wearable) tele-ECG systems, digital technologies, intellectualization and mobility of communications gave an evolutionary impulse, the potential to ECG telecommunications, not only in the tasks of primary signal processing (data) [3].

Modern multi-channel digital individual-type cardioregistrators are based on mobile devices, Bluetooth, WiFi, monitoring and surveys, pre-medical formation (screening) of conclusions and databases, data centers, special applications (clouds, web browser). Various criteria (both focused and interval estimation of deviations) and analysis methods (linear, nonlinear, fuzzy, heuristic, and expert) are used, and responses are automatically generated (without additional resources, especially time resources for personnel). The recorders are attached to the body (chest), which brings them closer to the diagnostic capabilities of implantable devices.

A non-invasive, psychologically comfortable system also vividly visualizes the results, connects with the data center on the "anywhere, at any time, on any device (channel)" principle. System intellectualization actualizes integration with Big Data and Data Mining systems [4,5], and neural systems.

Big Data + Data Mining actively penetrate medicine, allowing us to explore hidden (latent) connections in medical data. It is necessary that, in accordance with the paradigm of digital medicine and economics, the evolutionary potential should shift from software-technical, statistical aspects, trends, to intellectual-technological, predictive, support for Data Mining, Social Mining, Big Data, etc. This will enable intelligent analysis of data volumes six or more orders of magnitude higher, allowing us to solve problems that are beyond the capacity of traditional technologies for updating medical data.

In this paper, based on a system analysis of the Big Data capabilities, an approach to the examination of patients with atrial fibrillation in real mode and plethysmogram curves is considered. An intelligent statistical analysis of the plethysmogram wave peaks was performed using a defibrillator monitor (MindrayBeneheartD3), a statistical package (Statistica 10.0), and a Mann-Whitney criterion U-trait.

Setting the problem of atrial fibrillation

There is inconsistent activity, excitation in the atrial fibers (with a frequency of up to 600/min) with the loss of their mechanical systolic component during atrial fibrillation. As a rule, this leads to an increase in the frequency of the ventricular rhythm and sometimes to fluctuations in hemodynamics [6]. The situation is dangerous with cardiogenic thromboembolism, a multiple increase in the risk of stroke; ischemia is caused by defibrillation in 15% of cases, up to 25% with an age horizon of 80-89 years old.

The Framingham study notes hypertension and DM as significant predictors that increase the risk of atrial fibrillation by one and a half times. Due to the population prevalence of hypertension, the responsibility for the increase in cases of atrial fibrillation is high (14%), higher than other risk factors [7].

Systematic ECG monitoring revealed that fibrillation accompanies every twentieth case of acute stroke. This is significantly more common than a standard 12-lead ECG, and atrial fibrillation is latent (not diagnosed by symptoms) for a long time [8].The true population prevalence of fibrillation is likely closer to 2%, from 0.5% at 40-50 years of age and 6-15% at 80 years of age [9].

Data from 2010 indicate the prevalence of fibrillation in the global population in 20.9 million (men) and 12.6 million (women), respectively. The indicators are higher in developed countries [10]. The prevalence is projected to reach almost 17 million (215,000 cases diagnosed annually) in the EU population in 2030 [11,12].

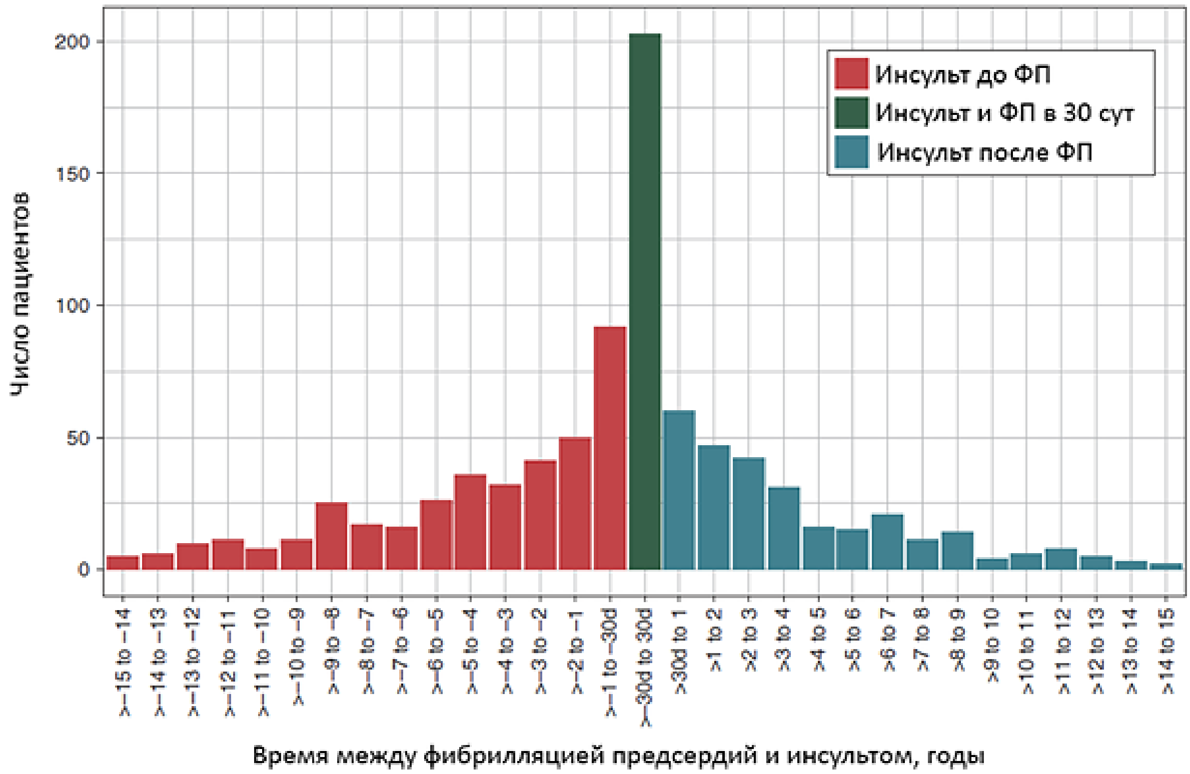
In the Russian Federation, atrial fibrillation annually spreads in relation to 2536 people per 100,000 population (3723,000 diagnosed cases), the number of hospitalizations - up to 1227,000, mortality - 12.3 per 100,000 population [13].

These statistics indicate that atrial fibrillation has become an urgent global risk problem, one of the key causes of heart failure, strokes, sudden deaths and cardiovascular diseases. Women are more likely to have a stroke than men if there are additional risks, especially for older adults [14].

The stroke is more severe, leading to disability, often death with fibrillation. About 20% of the stroke causes are fibrillation, and the "silent" (undiagnosed) version of it can cause "cryptogenic" strokes [13], and the risk of stroke in untreated patients is more than 30%. Clinical and epidemiological data demonstrate that fibrillation is a key independent factor of stroke. It increases the probability of risk by up to 5 times (after other factors). Strokes observed against the background of fibrillation are more frequent, increasing every 10 years: from 6.5% (50-59 years old) to 30.7% (80-89 years old)[14].

Ischemic stroke associated with atrial fibrillation is twice as lethal as without it, and functional deficiency in stroke is more pronounced, a high risk of thromboembolism is also more likely with an enlarged left atrium (decrease in the systolic functionality of the left ventricle) [15]. The time dependence of atrial fibrillation with stroke is shown in Figure 1 (data: CamenS., etal. EPEuropace, 2020, No.4. -pp:522–529).

Figure 1. Histogram of the relationship between stroke and atrial fibrillation



With fibrillation, the risk of stroke can be assessed on the CHA2DS2-VASc scale, which includes several key risk factors (age 75, female, diabetes mellitus, hypertension, heart failure or systolic dysfunction for the left ventricle, systemic thromboembolism or stroke, vascular disease) [16]. The higher CHA2DS2-VASc scores, the higher stroke risks (Figure 2, data: FribergL., et al. / / JACC, 2015, No. 65. - pp. 225-232) or vice versa.

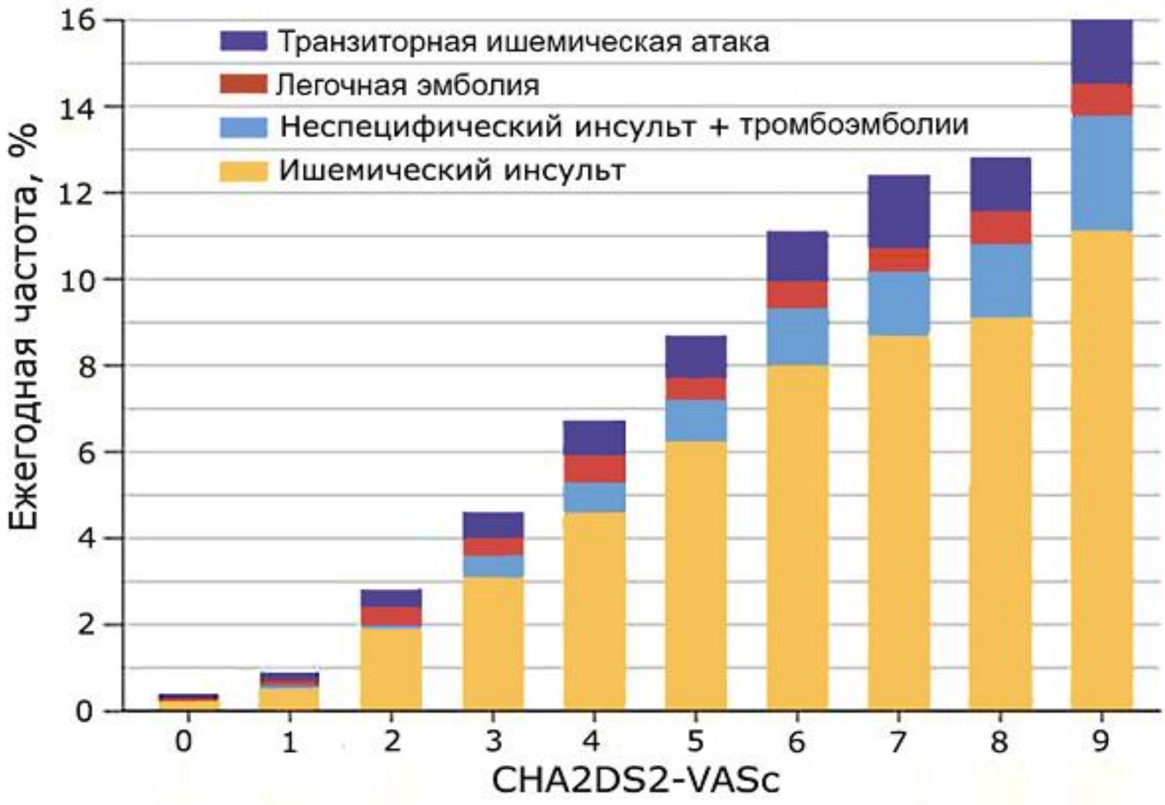


Figure 1. Stroke risks on the CHA2DS2-VASc scale

Big Data and data Data Mining in cardiovascular diseases

It is possible to classify ICTs used in medical problems [17] as systems that are:

1) cognitive (statistical, situation modeling, etc.);
2) infological (reference, consulting, management, etc.);
3) intellectual (analytical, expert, Data Mining, etc.);
4) training (distance, retraining and advanced training, etc.);
5) technological (medical and rehabilitation, clinical and diagnostic, etc.).

Other classification approaches are also possible, for example, for health care systems, administrative and organizational systems, medical institutions, etc.

The Unified Health Information System (UHIS) defines the main technological, medical and legal standards:

1) maintaining and processing documents;
2) restrictions, health protection criteria;
3) responsibilities of medical and support personnel;
4) network (local, global) support;
5) database security (clients, clinical trials, EDS, etc.)

The structuring abilities of the brain are incomparably higher than the speed of extracting and processing data from memory. Big Data (which is a well–established term) is intuitively clear to everyone, although there is also an underwater part of the "data iceberg", which consists (regarding our task) in poor structuring, lack of systemacy, multi-criteria nature of the acquisition and interpretation of data by patients, symptoms, risks and tools.

Big Data in medicine (healthcare) allows to intelligently analyze the following data:

1) diagnostic (clinical);
2) "sensor" (monitoring);
3) ambulance service;
4) regulatory criteria (especially in healthcare);
5) pharmacological, pharmacokinetic data;
6) genetic factors;
7) social (including health data security, trust), etc.

Big Data allows to identify and explore the functional and statistical relationships hidden in big data using Data Mining in modern medical information systems (MIS). This is the way to form a single data structure (for example, an index-table structure), to analyze their layers that were previously impossible to work with, not only because of a lack of computing power, but also because of the lack of relevant models and methods. For Big Data, it is possible to have a variety of data and a variety of applications in medicine (healthcare) that are not related to data.

This is facilitated by the following principles of using Big Data in medicine:

1) horizontality, any procedure, any method of data processing - we expand it when the volume of processed data increases;

2) locality, any network data is structurable, fault-tolerant processed "from any computer, device, at any time comparable to the time of communication with the storage server".

Social networks, professional online platforms (websites, forums, blogs) and screening are a rich source of medical data. Big Data updates 3D-visual and intuitively read "on the fly" atrial fibrillation data, consilium data, etc. For example, in a clinic, applying the patient's e-card, they leave personal and protected clinical (or screening) information in the memory of the center, Big Data, or data center, and the neuro-system analyzes it and makes a decision, for example, about an ischemic attack or an ischemic stroke. Mobile devices process data that is controlled, for example, by GPS or GLONASS signals. The client computer can process up to a terabyte of data every day. For example, using a Data Mining-based model for managing the flow of cardiovascular patients [18].

Results and analysis of statistical studies of ECG and plethysmogram data

Thirty patients with atrial fibrillation were examined in the Department of Anesthesiology and Resuscitation No. 2 of the State Medical Institution of the Republic of Kazakhstan "RKB named after N. A. Semashko". Two standard ECG leads and the plethysmogram curve were recorded in real time in patients, the curves were compared with each other. The R-R and inter-peak intervals (plethysmogram waves) were calculated with subsequent statistical processing. The ECG and plethysmogram were fixed with a Mindray Beneheart D3 defibrillator monitor.

The data was statistically processed using the Statistica 10.0 program. We used a nonparametric Mann-Whitney U-trait criterion. The data is presented as the median (Me) and the values of the I and III quartiles (QI-QIII). The differences were considered statistically significant at $p<0.05$. The values of the R-R interval and the interval between the peaks of the plethysmogram waves are expressed in seconds.

Let us discuss the main results of the conducted research. In the course of this study, the results obtained confirm the possibility of suggesting the presence of atrial fibrillation in the patient by analyzing the plethysmography curve. Statistical processing of the obtained data revealed no significant difference between the R-R intervals on the ECG and the intervals between the corresponding peaks of the plethysmogram waves (p-value=1.0).

The results obtained significantly expand the possibilities of early diagnosis of atrial fibrillation at home with the help of smartphones, watches, fitness bracelets and appropriate software.

Table 1. Patient statistics.

Attribute	R-R	Plethysmogram	p-value
Me(Q_1-Q_3)	0,52(0,4-0,88)	0,52(0,4-0,92)	1,0

The introduction of early detection of atrial fibrillation with daily screening at home and early access to medical care can significantly reduce the number of strokes caused by atrial fibrillation.

Big Data, Data Mining-analytics is used not only in personal monitoring, but also for the classification and categorization of research, for example, for identifying a prognostic model (situational modeling) of cardiovascular diseases, detecting the causes of atrial fibrillation, including using sensors worn by patients, and the API and web support.

Thanks to Big Data, it is possible to move away from expert-heuristic identification of the disease, and most importantly, to make it more accurate, probabilistically estimated, a priori predictable.

Conclusion

Big Data, Data Mining and MIS allow us to identify relationships, structures, and adaptively manage medical and healthcare processes, including medical business processes. For example, for their integration, registration, information, service, management, audit, security, and, most importantly, support for the decision-maker.

The results increase the evolutionary potential of early diagnosis of atrial fibrillation (including at home, using a gadget and mobile applications). For deviations, heart rhythm disorders, individual monitoring will allow us to implement identical clinical measures, to isolate those who need additional operational clinical examination from the flow.

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