Behavioral Parameters as COVID-19 Signs. New Opportunities and Old Problems of Medical Diagnostics

Viktor A. Minkin[1], *Alexander A. Kosenkov*[2]

[1] Elsys Corp, St. Petersburg, Russia, minkin@elsys.ru

[2] State Research Center — Burnasyan Federal Medical Biophysical Center of Federal Medical and Biological Agency (SRC — FMBC) of Russia, Moscow, Russia

Abstract: *Measuring of human behavioral parameters based on vibraimage technology for medicine applications are considered, including: diagnostics of COVID-19, monitoring the effectiveness of vaccination against COVID-19 and post-covid-19 rehabilitation. Variants of artificial neural networks (ANNs) training are given, depending on medical diagnostics tasks. The possibility of COVID-19 diagnosis at the stage of disease start and end using behavioral parameters has been shown. Monitoring of vaccination effectiveness against COVID-19 by measurable behavioral parameters is given. The possibility of post-covid-19 state control using behavioral parameters has been shown. The analysis of behavioral characteristics advantages over traditional biochemical and biophysical methods in medical diagnosis and disease treatment monitoring was done.*

Keywords: *COVID-19, vibraimage, behavioral parameters, medical diagnostics, disease, symptoms, vestibular-emotional reflex, biometrics, machine learning, ANN, AI, VibraHT.*

Introduction

Traditionally, humanity has opposed material and spiritual, matter and energy, considering these concepts opposite. From the point of view of modern physics, mathematics and information theory, the difference between these concepts is not so great, any object can have material, energy and information characteristics. The founder of cybernetics, Norbert Wiener, argued in 1948 “Information is information, not matter or energy. No materialism which does not admit this can survive at the present day” (Wiener, 1948). Unfortunately, what was said almost 100 years ago can be repeated now with even greater urgency. Modern medicine is currently completely focused on the material (and not informational) approach to disease, diagnosis and treatment methods. Weak attempts to portray digital medicine as an impartial science, using biophysical, biochemical and behavioral data equally, only underline this inequality (Alber et al., 2019). Most advances and failures in modern medicine are based on obtaining material data from biochemical or biophysical analyzes, including in the diagnosis of COVID-19 (Zhang et al., 2020; Soares et al., 2020; Erdem & Aydın, 2020; Hussain et al., 2020; Jin et al., 2020; Wynants et al., 2020; Struyf et al., 2020; Jimenez-Solem et al., 2021). While the behavioral parameters of a person are almost completely ignored by modern medicine, although they are the basis for the diagnosis of any disease, the first classic question of a doctor to a patient is — what are you complaining about? Few of the patients complain about biochemical tests (sugar, cholesterol, etc.). Biochemical changes in the body are mostly secondary, it is the behavioral characteristics that are primary, for example, fatigue, headache, nausea, cough — the so-called symptoms of

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the disease. However, symptoms are the same behavioral parameters having deviation from the norm if the norm is correctly defined and the behavioral parameters are measured by a physical method. Such method of behavioral parameters measuring offered by vibraimage technology (Minkin, 2020), determining various psychophysiological parameters when measuring reflex micromovements of a head.

Human vestibular system autonomously supports a head in an upright state with the help of constant contraction of the cervical muscles, and any pathological processes make changes in the work of the vestibular system. This phenomenon called vestibular-emotional reflex (Minkin & Nikolaenko, 2008; Minkin, 2020), since emotional states also affect the parameters of micromovement of the head, for example, an aggressive state increases the frequency of reflex micromovements (Lorenz, 1963). A person is always under the influence of many different external factors (physical, chemical, biological, emotional, informational and others), which bring or do not remove the physiological systems of a person from an equilibrium state. The functioning of physiological systems is based on a variety of feedbacks, the regulation of equilibrium (biological, physical, chemical) in the body is provided in various terminology by homeostasis (Cannon, 1932), allostasis (McEwen, 2000), homeokinesis (Halberg, 1969; Minkin & Blank, 2019; 2021) or interoception (Chernigovsky, 1985; Petzschner et al., 2021), depending on the choice of a model for achieving equilibrium. A simplified equilibrium state regulation model (regulation of the internal environment) shown in a variety of publications, from textbooks to scientific articles, on modeling physiological processes (Selye, 2013; Novoseltsev, 1978; McEwen, 2000). We do not consider necessary to complicate the structural diagram of the effects on a person, because it is the detail of the presentation, in my opinion, that hinders the understanding of the general principles of health or disease. External influences lead to changes inside the body. Body defense mechanisms (as immunity) coordinate reversible of changes; they determine the correctness of treatment, which is also an external effect.

Figure 1 shows a generalized block diagram of the material and informational impact on a person in the process of treating an arbitrary disease. Biometric standards (GOST ISO/IEC 2382-37-2016) divide all measurable characteristics of a person into biological (material) and behavioral (informational), therefore we will adhere to this standard terminology, including for medical diagnostics, since medical research methods and analyzes underlying medical diagnostics should be considered as separate area obtaining biometric characteristics of a person.

On Figure 1, the patient is presented in the form of physiological systems and blocks having control signals (interoception), and each element of such a scheme has a two-way communication with any other element of the system. It follows from the above diagram that any change in an arbitrary block leads to certain changes in all other elements of the system. Consequently, any disease leaves its unique imprint on the functioning of each physiological system and, for example, control of the vestibular system, could be sufficient for the diagnosis of an arbitrary disease.

The purpose of this work is to compare various methods of analyzing medical (material and information) data during a disease and study the possibility of behavioral parameters using for medical diagnostics of a disease, control treatment process, rehabilitation process monitoring and assessing the effectiveness of COVID-19 vaccination by vibraimage technology and ANN learning.

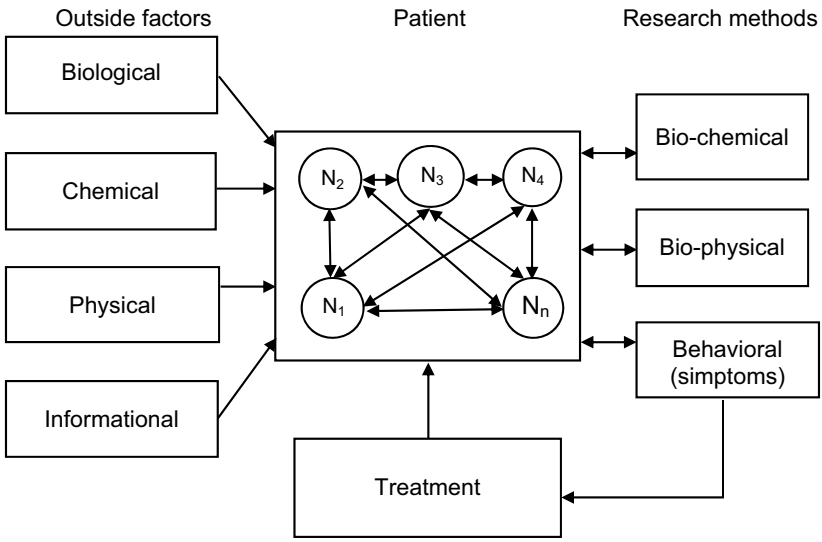


Fig. 1. *Structural diagram of material and informational impact on a person in the process of treating an arbitrary disease. N1–Nn — physiological systems and different levels of exchange of control signals in the human body*

Materials and Methods

The method for measuring 40 behavioral parameters is based on vibraimage technology (Minkin, 2007; 2020; Akimov & Minkin, 2021), is also used for medical diagnostics (Blank et al., 2012; Minkin & Bobrov; 2020) and more effective by using trained ANNs (Bobrov et al., 2020; Minkin et al., 2020; Akimov & Minkin, 2021). For capturing information about the micromovements of a human head, Microsoft LifeCam Studio webcam placed one meter away from a patient, sitting in front of the webcam for 3 minutes. Webcam was connected to a computer with Intel Core i7 processor, on which VibraHT (Minkin et al., 2020) program is installed, determines behavioral parameters and health characteristics by analyzing the micromovements of the human head using a pre-trained ANN. The measurement of patient's behavioral parameters was carried out at different periods of the COVID-19 disease, divided into 4 stages, shown in Table 1, similar to the reaction to a stress factor presented by Hans Selye (Selye, 2013).

Table 1

Different periods of COVID-19 disease, divided into 4 stages for behavioral parameters database formation

Disease stage	Incubation period, days	Active phase of the disease, days	Recovery process, days	Rehabilitation process, (months)
Duration, days (months)	1–7	14–30	7–30	1–6

In total, 331 measurements of patient's behavioral parameters at different stages of COVID-19 disease were carried out. Similar to the patient group measurements, 331 behavioral measurements were taken for COVID-19-free control (referenced) group. Total database contained 662 results for measuring behavioral parameters (331 results in the patient group and 331 results in the control group). To study the behavioral parameters on COVID-19, ANN learning was done on all 662 measurement database and less measurement quantity taken for individual stages of the COVID-19 disease study.

Let's imagine how the proposed method works using the following example. The patient comes to the doctor and complains about 2481 signs of his poor health. The doctor says: "OK, now I will examine you." And in one minute, he quantitatively determines each of the 2481 signs, comparing them with the norms of various diseases that he has. This is exactly how trained ANN (Akimov & Minkin, 2021) works with continuous (5 counts of each parameter per second) measurement of 40 behavioral parameters in one minute. ANN template files for detecting COVID-19 and diagnosing post-covid-19 symptoms are given on supplementary material to this article.

Diagnosis of COVID-19 by Behavioral Parameters

The principles of COVID-19 early diagnosis using behavioral parameters, and artificial neural network (ANN) learning, were previously described (Minkin et al., 2020; Akimov & Minkin, 2021). One of the not less important questions than early diagnosis of the disease is the question to which there is currently no unambiguous answer — when does a specific patient who has undergone COVID-19 cease to be infectious to others (Prakash, 2020)? The presence of a negative PCR test result is unlikely to indicate that the patient is not contagious, most likely indicates the transition of the disease to the final phase (Chan et al., 2020). The presence of an increased level of IgM antibodies also cannot be evidence of the continuation of the infection. The production of antibodies occurs with a certain inertia, and the time difference between receiving a negative PCR test and a negative IgM test result in COVID-19 can be several months (Arevalo-Rodriguez et al., 2020; Liu et al., 2020; Sheikhzadeh et al., 2020). Therefore, in most cases, the decision to discharge a patient is made by a doctor, based on individual information, in each specific case. Let us consider case (1) how objectively a decision can be made by a trained ANN about the end of COVID-19 disease in the presence of regular measurements of behavioral parameters by the VibraHT program (Minkin & Bobrov, 2020; Minkin et al., 2020). Patient 1 (male, 41 years old, negative PCR test received on February 15, 2021, 18 days after the onset of COVID-19 symptoms. The last positive PCR test received on February 8. Normal body temperature 36.4–36.5°C from February 10, discharge from the doctor — from February 20).

When entering the data of the behavioral parameters of this patient to ANS processing, the AI determined the data of the behavioral parameters obtained on February 15, 16, 17 as a disease, and on February 18 and 19 as the absence of COVID-19, i. e. close enough to the doctor's discharge. Note that COVID-19 diagnostic program based on behavioral parameters signs, determined the patient as sick and, probably, capable of infecting others within three days after a negative PCR test. The measurement data of patient 1 at the end of COVID-19 disease are shown in Table 2.

Table 2

COVID-19 diagnostic data during patient recovery (case 1). The HealthTest page of the VibraHT program

Date	Σ[R], score (norm >20,0)	Σ[ΔM], score (norm <4,0)	Behavioral signs of COVID-19, % (norm <50)	T, °C (norm <37.5)
2021–02–16 11_08_14_M	49,00	2,59	100,00	36,6
2021–02–17 10_23_46_M	60,35	2,47	100,00	36,6
2021–02–18 10_13_43_M	33,49	1,80	0,00	36,4
2021–02–19 09_49_47_M	33,93	1,53	0,00	36,4

Σ[R] — total correlation between behavioral parameters. Σ[ΔM] — conformity of behavioral parameters to the general pattern. Statistical norms for behavioral parameters indicated in parentheses. The behavioral signs of COVID-19 are determined by ANN based on 40 input behavioral parameters and COVID-19 database (662 measurements).

Shown sharp transition from 100% probability of COVID-19 disease in Table 2, obtained on February 17, to zero probability, obtained on February 18, is most likely determined by the insufficient size of the database during ANN learning. With larger training database (higher 2500 measurements), the transition from illness to recovery should be smoother. It should not be assumed that ANN and AI can be taught to any result, by arbitrarily forming a database of patients and control at their own discretion. An attempt made to form a database of behavioral parameters measurements of the patient (1) by the formal moment of the patient's discharge from February 20 inevitably gave 2 extra false positive errors based on the measurement results on February 18 and 19. Database forming to the moment of negative PCR test, 2 additional false-negative errors inevitably appeared based on the results of measurements on February 16 and 17. Thus, minimizing ANN errors when analyzing an already trained database shows a more accurate end of the disease than traditional biochemical methods of analysis, for example, the result of the PCR test.

Monitoring of Patient's Behavioral Parameters after Vaccination against COVID-19 by Sputnik V Vaccine

It was not random given in the first part of this paper Table 1 with various stages of the disease. ANN training based on the measurements results made in a certain part of the disease makes the diagnostic program more sensitive to the selected part of the disease, since the symptoms, and hence the behavioral parameters, change markedly at different stages of the disease. For example, look monitoring of the behavioral parameters of patient 2 (woman 39 years old, the first vaccination with the Sputnik V vaccine was made on February 12, 2021). Monitoring after the first vaccination with the Sputnik V vaccine by standard COVID-19 diagnostic program VibraHT, trained on a full database

(stage 1–3, 662 measurements) showed changes in behavioral parameters, but did not show the identification of COVID-19 signs, which, in general, was expected. However, the study of patient 2 by ANN learned on shortened database (stage 1–2, 520 measurements) without stage 3 (recovery process) showed a fundamentally different result, shown in Table 3.

Table 3

Measurement data of behavioral parameters during vaccination of a patient (case 2) with the Sputnik V vaccine

Date	Σ[R], score (norm >20,0)	Σ[ΔM], score (norm <4,0)	Behavioral signs of COVID-19, % (norm <50)	T, °C (norm <37.5)
2021–02–12 15_52_02_M	20,69	1,29	0,00	36,6
2021–02–13 10_43_16_M	21,69	1,89	0,00	36,6
2021–02–15 10_52_50_M	24,08	1,27	99,94	36,4
2021–02–16 13_52_15_M	24,11	2,13	99,99	36,4
2021–02–17 15_02_17_M	20,97	2,59	100,00	37,5
2021–02–18 14_55_56_M	19,78 (>20,0)	1,44	0,00	36,8
2021–02–19 13_57_41_M	13,20 (>20,0)	1,55	0,00	36,6
2021–02–20 11_36_49_M	13,63 (>20,0)	1,61	0,00	37,8
2021–02–21 14_35_26_M	16,12 (>20,0)	1,36	0,00	36,6
2021–02–22 17_06_21_M	22,79	1,01	0,00	36,4
2021–02–24 15_14_03_M	28,53	2,43	0,00	36,5

Σ[R] — total correlation between behavioral parameters. Σ[ΔM] — conformity of behavioral parameters to the general pattern. Statistical norms for behavioral parameters are indicated in parentheses. The behavioral signs of COVID-19 are determined by ANN based on 40 input behavioral parameters and COVID-19 short database (520 measurements).

The results in Table 3 show that the vaccinated patient (2) indicates behavioral symptoms of COVID-19 on the third day after vaccination, these symptoms lasting for 3 days. Then there were problems of a general deterioration of the physiological state lasting 4 days. The patient's normal psychophysiological state was restored on the 8th day after the first Sputnik V vaccination according to behavioral parameters measurements. The patient's body temperature changed was not so informative and it is difficult to assess the change in the patient's condition using it.

Rehabilitation after Illness. Rehabilitation Problems of Post-COVID-19 Patients

Rehabilitation after serious diseases is one of the areas of modern medicine for the patients having a heart attack or stroke. The COVID-19 pandemic revealed such a wide range of consequences in patients after an illness (Barker-Davies et al., 2020), which turned out to be quite unexpected for specialists. Physicians traditionally use biochemical and biophysical methods of analysis to control post-covid-19 changes, but there is currently no understanding of the patterns of common post-covid-19 symptoms (Barker-Davies et al., 2020; Kabi et al., 2020). In my opinion, this is due to the fact that biophysical and biochemical methods of analyzing an organism are aimed at identifying local signs and are focused on identifying a certain physical quantity or biochemical indicator. While the control of behavioral parameters allows to assess the totality of many parameters and characterize the psychophysiological state as a whole.

Consider case 3 (woman, 63 years old, suffered COVID-19 in July 2020), while, after almost six months, the patient did not return to normal after the illness and complains of multiple post-covid-19 symptoms, including rapid fatigue, dizziness, pain in heart, muscles and joints. Testing the patient with standard VibraHT program did not show signs of COVID-19, while testing the patient with a program with excluded data from the first and partially the second phase (510 measurements) of the disease showed persistent symptoms of COVID-19 (Table 4).

Table 4

Measurement data of behavioral parameters during post-ovarian rehabilitation of a patient (case 3)

Date	Σ[R], score (norm >20,0)	Σ[ΔM], score (norm <4,0)	Behavioral signs of COVID-19, % (norm <50)	T, °C (norm <37,5)
2020–12–24 10_39_53_M	20,94	4,00	99,99	36,6
2020–12–24 10_45_03_M	24,37	4,09	99,77	36,6

Σ[R] — total correlation between behavioral parameters. Σ[ΔM] — conformity of behavioral parameters to the general pattern. Statistical norms for behavioral parameters are indicated in parentheses. The behavioral signs of COVID-19 are determined by ANN based on 40 input behavioral parameters and COVID-19 short database (510 measurements).

Note that behavioral parameters measurements results, taken with a break of several minutes, show similar results, which emphasizes the relative stability of the post-covid-19 state. In addition, for this case, I will give an expanded table of behavioral parameters measured by the VibraHT program and shown in Figure 2.

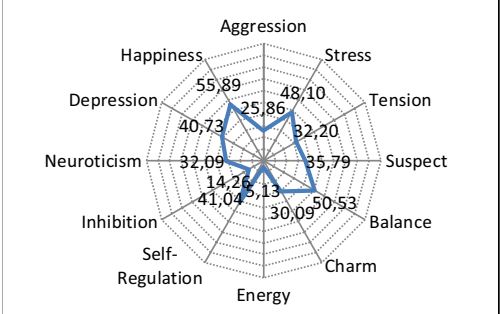
Psychophysiological State Measurement Results

Name	Case 3	**ID**	XXX
Gender	G	**Date**	24.12.20 10:48
Age	63	**Σ Vi**	22,6152

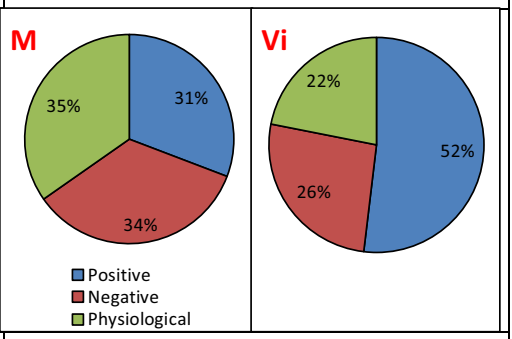
10 Parameter Results

Parameter	Min	Avg	Max	Vi	Parameter	Min	Avg	Max	Vi
Aggression (20 ~ 50)	18,1	25,8577	43,5	15,2	Stress (20 ~ 40)	36,3	48,097	56,4	9,5
Tension (15 ~ 40)	8,9	32,1996	51,7	28,0	Suspect (20 ~ 50)	26,2	35,7864	44,0	10,4
Balance (50 ~ 100)	17,5	50,5315	69,0	14,4	Charm (40 ~ 100)	18,1	30,0934	78,3	54,9
Energy (10 ~ 50)	2,7	5,133	9,6	31,5	Self-Regulation (50 ~ 100)	22,0	41,0444	68,2	24,4
Inhibition (10 ~ 25)	8,9	14,2604	25,2	22,5	Neuroticism (10 ~ 50)	2,0	32,0932	46,8	15,2
Depression (20 ~ 50)	33,3	40,73	46,9	8,9	Happiness (50 ~ 100)	50,1	55,89	76,3	6,2

Parameter Chart

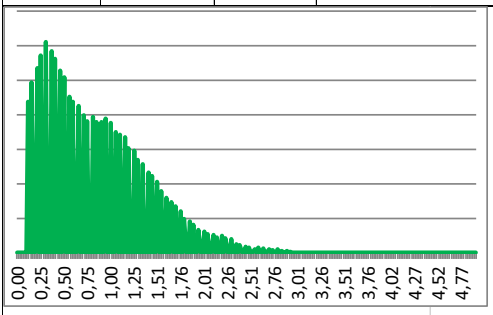


Emotion distribution Chart



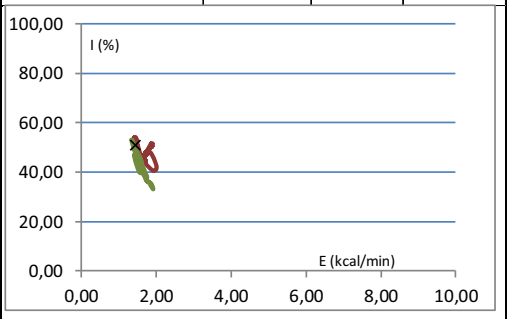
Frequency Histogram

Mf	0,827	S	0,550



Psy variability - Mental basal metabolism

Psy change rate	32,9-54,2	Kcal/min	1,3-2



Result [Quality 100% / 6]

Extraversion	**55,9292**	**Stability**	79,2555

Fig. 2. *Typical pattern of behavioral parameters for a post-covid-19 patient. Measurement page of VibraHT program*

Pay attention to the Frequency Histogram of Figure 2. This asymmetric distribution with a low-frequency maximum and extended right side of the frequency distribution is quite typical for patients with COVID-19 and post-covid-19 disorders. The normal Gaussian distribution for vibration frequency is standard for a normal psychophysiological state (Minkin, 2020).

Discussion

The results of behavioral parameters application for medical diagnostics presented in this article show that behavioral parameters could be more informative for the diagnosis of severe diseases than the traditionally used biochemical or biophysical analyzes. This relatively paradoxical claim has a rationale. The behavioral characteristics of a person are determined by a set of biophysical and biochemical processes occurring in the human body. Each specific biochemical or biophysical analysis determines with some accuracy only one component from the general psychophysiological state of a person, even if it is very important for diagnosing a disease, for example, the concentration of COVID-19 viruses in PCR analysis. However, the human body is an extremely complex system (Tamar, 1972; Novoseltsev, 1979; McEwen, 2000; Cacioppo et al., 2007) with many feedbacks that determine the body's immune and other capabilities to fight any infection or pathology. Therefore, attempts to diagnose and control the disease by separately taken point values of material parameters are inferior in informativeness to the control of behavioral parameters, covering the interaction of all physiological systems and human metabolic processes. Modern information technologies, sharpened on the processing of big data, are more suitable for the diagnosis of complex diseases, since each person is a direct bearer of a huge number of information and energy connections and dependencies. The number of physiological and informational processes occurring in the human body every second exceeds the capacity of modern processors, and the processing of point information that biochemical and biophysical analyzes can give cannot provide accurate information about the norm and pathology in the case of complex diseases. This explains the fact that, more than a year after the start of the pandemic, the entire medical community cannot give a definite answer to many questions related to COVID-19 (Weston & Frieman, 2020; Maggi et al., 2020). At present, it is impossible to confidently predict the resistance of a particular person to infection with COVID-19 (Verity et al., 2020), the severity of COVID-19 for a particular person, and to determine the means of rehabilitation after the COVID-19. Those statistics (Verity et al., 2020; Wu et al., 2020), which are obtained on the risk factors for COVID-19 severity (gender, weight, chronic diseases), also cannot be attributed to biophysical or biochemical test results and this is hardly a coincidence.

The progress of modern science and technology is not accidentally associated with the processing and transmission of large amounts of data, but for some reason, in the minds of society, the processing of big data is primarily associated with the receipt of information from a multitude of people or other information objects. While every person is constantly processing and transmitting huge amounts of data, and on this principle vibraimage technology was developed. Vibraimage system processes more than 30 MB of information every second (3 minutes of measurement is about 5.4 Gb of information) and transforms this big data stream in a limited number (currently 40) behavioral parameters. Then AI

embedded in the VibraHT program determines 2481 values of the significance coefficients between 40 behavioral parameters and compares them with a template determined from the database of a specific disease. Moreover, 1–3 minutes of measuring behavioral parameters is not a limit for the diagnosis of COVID-19 or another disease. Diagnosis of a disease can be carried out in real time, since the process of comparing behavioral parameters with a disease template is carried out in a fraction of a second, and a few seconds are enough for contactless measurement of a person's behavioral parameters (Minkin, 2020).

This approach makes possible to measure behavioral parameters that are inextricably linked with the functioning of all physiological systems of a person, and therefore objectively characterize minor and significant changes in a human body. That is why, achieved in terms of behavioral parameters, 99% accuracy of databases discrimination of patients with COVID-19 and control group (Minkin et al., 2020) exceeds the accuracy of diagnostics using biomedical PCR methods and IgM-IgG antibodies (Bastos et al., 2020).

Behavioral parameters represent a generalization of biophysical and biochemical material processes, behavioral information seems to be immaterial, but it is based on material biological, physical and chemical processes. Sigmund Freud wrote that a person does not have random movements and slips (Freud, 1900). Ivan Sechenov said that every thought (which he regarded as material process) has a muscular manifestation (Sechenov, 1863). Charles Darwin emphasized the informativeness of reflex movements in the formation of a person's emotional state (Darwin, 1872). Unfortunately, the systematic approach and understanding of the behavioral parameters significance of the 19th century was replaced by narrowly specialized material approaches of the 21st century. Therefore, until modern society revises the clearly discriminatory approach to such small use of behavioral parameters in medicine and, above all, for medical diagnostics (Wynants, 2020; Arevalo-Rodriguez, 2020), it is difficult to expect rapid significant successes in the fight against the COVID-19 pandemic and other complex diseases, including new viral infections. For hundreds of material (biophysical and biochemical) methods publications for COVID-19 diagnosis, also using ANN and AI technologies (Wynants, 2020; Hussain et al., 2020), were developed only 2 diagnostic methods based on behavioral parameters (Laguarta et al., 2020 ; Minkin et al., 2020). In my opinion, this inequality is primarily determined by the existing distrust of the modern medical community in information technologies for processing big data, which are not associated with the material causes of diseases. However, a non-obvious connection does not mean its absence.

This article was written a year after the WHO recognized the COVID-19 epidemic as a pandemic (Tedros, 2020) and more than a year after the decoding of the COVID-19 virus genome (Chen et al., 2020). Therefore, the decoding of COVID-19 virus genome on the molecular-genetic level could not stop the pandemic, which is going according to its natural law, mortality from the disease remains approximately at the same level as at the beginning of the epidemic (Woolf et al., 2021). Only measures known since the Middle Ages, such as strict quarantine and disinfection, have a noticeable effect on the spread of infection, while ongoing vaccination has not yet significantly affected the spread of COVID-19 and many experts express doubts about its effectiveness (Kim et al., 2021). Medicine needs modern methods of dealing with new infectious diseases, and only an integrated approach (prevention, diagnosis, treatment, vaccination) can be effective in the treatment of complex diseases (Ghebreyesus & Leyen, 2020).

Conclusion

Perhaps some readers will pay attention to the insufficiently complete disclosure of each specific case of disease diagnosis, the effectiveness of vaccination or post-ovarian rehabilitation given in this article. Of course, each of the above cases is worthy of a more detailed description. However, we deliberately shift the focus from each specific medical case to a general approach to the need to use behavioral parameters for medical diagnostics. The proposed approach does not negate the existing material and traditional biochemical and biophysical analyzes, which successfully solve many problems and help in the diagnosis of most diseases. Moreover, they are necessary for the initial setup and training of the ANN and AI with behavioral parameters data. However, if we evaluate the costs of going biochemical analyzes, the time of obtaining the result, the accuracy of diagnostics, the environmental friendliness of the production of drugs, it turns out that medical diagnostics in terms of behavioral parameters significantly surpasses all known biochemical and biophysical methods of analysis. Indeed, none of the existing methods of biochemical or biophysical diagnostics of COVID-19 can provide an answer to such essentially different issues of early diagnosis of the disease, monitoring the effectiveness of vaccination and post-covid-19 rehabilitation. The definition of such different pathologies using a set of measured behavioral parameters cannot be random. It shows the highest informativeness of behavioral parameters for detecting any pathology or any disease, since COVID-19, from the point of view of information theory, is no different from other diseases. Each disease carries its own signs or has its own material (physical, chemical, biological) imprint, which is reflected in its symptoms, and therefore behavioral parameters. AI and ANN find this unique imprint by simply sorting through the dependencies between behavioral parameters, almost as intuitively as a dog smells a specific smell from COVID-19 patients (Jendrny et al., 2020).

It is difficult to imagine how much effort, material resources and research are spent on the preparation of covid passports and other means of disease control, which are relevant only at the time of issue. No one can 100% guarantee that a tested or vaccinated person will not become infected the next minute after receiving a health passport. Instead, it is advisable to carry out operational control (1–3 minutes or less) COVID-19 at borders, airports, public events using ordinary computers or even mobile phones. Solving any problem in real time is always better than being late in answering an emerging challenge.

The proposed transition to behavioral parameters measurement for medical diagnosis of any disease will require a huge amount of research to confirm the declared results, but if successful, humanity can get its hands on a much more effective and low-cost diagnostic method that has no analogues in terms of its range of application. The possibility of remote, contactless, fast and cheap diagnosis of any disease deserves any investment. Perhaps in 50 years, any contact biochemical analysis and diagnosis such as blood sampling or contact with the nasopharynx will be perceived approximately in the same way as today we perceive treatment with bloodletting or mercury (Yanin, 2000), which were used by official medicine from the 16th to the 20th century. To do this, it is necessary to review the existing ethical restrictions on the transfer and processing of non-personalized medical information, of course it is not a simple way.

The rapid development of biometric technologies was facilitated by open competitions for the processing of standard databases of biometric data (fingerprints, faces), held by public and private companies and allowing to select the most effective identification algorithms (https://www.nist.gov/biometrics). The creation of open databases of behavioral parameters, which has already begun (Minkin, 2020), should be accompanied by linking traditional medical analyzes with a confirmed diagnosis of unnamed patients to the same open databases. This approach will allow parallelizing the efforts of different teams and achieving the solution of many problems in the shortest possible time and with transparently proven efficiency.

Supplementary material

The ANN calculation files for detecting COVID-19 and diagnosing post-covid-19 symptoms given at https://psymaker.com/downloads/CovidANN.zip

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