Title

A mental health assessment method based on emotion level derived from voice

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Abstract

Background: In many developed countries, mental health disorders have become a problem, and the economic loss due to treatment costs and interference with work is immeasurable. Therefore, a simple technique must be developed to determine individuals’ depressive state and stress levels. Voice analysis using smartphones is not only noninvasive, it does not require a dedicated device; thus, it can be performed conveniently and remotely. Consequently, we developed a method to assess individuals’ mental health levels using emotional components contained in the human voice.

Methods: We proposed two indices of mental health: a short-term index (vitality) and mental activity calculated from long-term trends in vitality. We used the voices of healthy individuals (men: n = 10, M_{age} = 42.7 ± 6.0 years; women: n = 4, M_{age} = 35.0 ± 14.4 years) and patients with major depression (men: n = 19, M_{age} = 43.7 ± 11.0 years; women: n = 11, M_{age} = 53.9 ± 8.2 years). For patients, simultaneously with voice collection, specialists assessed current depression severity using the Hamilton Rating Scale for Depression (HAM-D).

Results: A significant negative correlation existed between the vitality extracted from voice and HAM-D score (r = -0.33, p < .05). We could discriminate the voice data of healthy individuals and patients with depression (judged as moderate or severe by the
specialists) with high accuracy using vitality (p = .0085, the area under the curve (AUC) of the receiver operating characteristic curve = 0.87). However, there was no significant difference between the vitality of the healthy individuals and the patients judged to be the “no depression group with almost no depressive symptoms,” even if they were outpatients with depression (p > .1, AUC = 0.64).

**Conclusions:** We developed a method to estimate stress through emotion instead of analyzing stress directly from voice data. By daily monitoring of vitality using smartphones, we can encourage hospital visits for people before they become depressed or during the early stages of depression. This may lead to reduced economic loss due to treatment costs and interference with work.

**Trial registration:** Not applicable.

**Keywords:** mental health assessment, vitality, mental activity, voice emotion analysis, non-invasiveness

**Background**

In many developed countries, mental health disorders have become a problem [1], and the economic loss due to treatment costs and interference with work is
immeasurable [2]. Therefore, a simple technique to determine individuals’ depressive
state and stress level is desired.

Self-administered psychological tests, such as the General Health
Questionnaire (GHQ) [3,4] and Beck Depression Inventory (BDI) [5,6], can be used as
screening methods for patients with mental health disorders. In addition, a stress-check
method that uses biomarkers in saliva [7] and blood has been proposed [8]. Although
self-administered psychological tests are useful for early detection and as diagnostic
aids, there is a problem with reporting bias—in which specific information such as
smoking history and medical history are selectively suppressed or expressed by
participants [9]. Stress-check methods that use biomarkers also have problems such as
the cost of the test and the burden on the participants during specimen collection; i.e.,
they are not convenient.

On the other hand, with the recent widespread use of smartphones, pathological
analysis using voice data has become popular [10-12]. Voice analysis using
smartphones is not only noninvasive, it does not require a dedicated device; thus, it can
be performed conveniently and remotely.

The relationship between mental illness and voice has been observed in
previous studies; e.g., studies regarding the speaking rate of patients with depression
[13-15], studies on switching pause and percent pause of patients with depression [15,16], etc. There are also studies in which Lyapunov exponents and Kolmogorov entropy for the voice of patients with depression were measured using chaos analysis [17]. A study that used frequency analysis showed that the shimmer and jitter in vowels as voiced by patients with depression were higher than those of healthy people, and the first and second formant frequency were low [18]. Zhou and colleagues proposed a new feature derived from the Teager energy operator for the classification of voices under stress [19]. In another study, a method was proposed to assess mental health from envelope information for pitch and speech waveforms [20].

On the other hand, stress is known to have an impact on emotions [21], and a method is being developed to estimate stress through emotion instead of analyzing stress directly from voice data [22-24]. Mitsuyoshi and colleagues [22] proposed an algorithm that estimates the expression of emotion from emotion components of the voice—the vocal affect display. In addition, they experimentally analyzed the relationship between this index and stress and estimated individuals’ stress level from their voice. In this study, sensibility technology (ST) that analyzes emotion in speakers’ voices was used [25-27]. The present study proposes a method to assess the mental
health of a speaker from the emotional components in his or her voice using ST with a focus on the relationship between mental health and emotions.

Methods

Acquisition of Voices

In this study, we collected voice data in two categories—healthy individuals and outpatients with depression. All participants provided written consent. Voice acquisition of the patient group was performed intermittently from August 2013 to October 2014 with outpatients at Kitahara rehabilitation hospital in Japan. Voices were recorded during patients’ conversations with physicians during examination. All data were then confirmed audibly; overlaps with other speakers and background noises were removed manually.

Voices of healthy people were acquired from February to mid-May 2015. During the acquisition period, participants worked normally at their jobs without visiting medical facilities for a mental illness. Voice acquisition was continuously performed once every several days; at each time, 14 types of fixed phrases were read aloud twice. Voices were recorded in a quiet environment with little background noise.

Voices were recorded by a gun microphone (AT9944: audio-technica, Tokyo, Japan) placed approximately 100 cm from participants, or by a pin microphone
(ME52W: OLYMPUS, Tokyo, Japan) attached to the chest at approximately 15 cm from participants’ mouth. The recording device was MS-PST1 (NORITSU KOKI, Wakayama, Japan; not commercially available).

Table 1 shows participants’ information per group. It should be noted that the number of participants and the number of data differed because data may have been collected multiple times from the same participant on different days. The average number of data collected per healthy person were 24.4 ± 33.3 for men and 6.3 ± 6.1 for women. For patients with depression, they were 6.0 ± 2.9 for men and 6.8 ± 3.2 for women. These collected data were used to create algorithms to calculate vitality and mental activity.

| Group             | Sex      | Number of participants | Mean age     | Number of data |
|-------------------|----------|------------------------|--------------|----------------|
| Healthy           | Male     | 9                      | 42.9 ± 5.6   | 220            |
|                   | Female   | 4                      | 33.3 ± 15.4  | 25             |
| Major depression  | Male     | 4                      | 54.0 ± 12.0  | 24             |
|                   | Female   | 5                      | 49.4 ± 15.4  | 34             |

Regarding the above-described recorded voice, a healthy person’s voice is a fixed-phrase utterance. On the other hand, a patient’s voice is a free speech in the form of dialogue with a doctor, and the type of speech differed between a healthy person and a patient. Further, the recording location differed. To unify both speech types and
recording environments, data for algorithm verification were collected at the National Defense Medical College Hospital in Japan with participants’ consent. Participants were informed that the anonymity and confidentiality of their data were guaranteed, and that they were free to withdraw at any time. Participants were not rewarded for their participation.

First, from December 2015 to June 2016, fixed-phrase reading voices were collected from outpatients with major depression. Table 2 shows 17 types of Japanese fixed phrases that were used for recording. At the time of voice collection, specialists evaluated patients’ depression severity using the Hamilton Rating Scale for Depression (HAM-D) [28]. The HAM-D is not a self-assessment-type psychological test; rather, experts such as doctors evaluate the characteristic items of depression symptoms. The purpose of the HAM-D is for a professional to objectively quantify an individual’s depressive state. On the other hand, for voices of healthy individuals, in mid-December 2016, the same fixed-phrase reading voices as the patients were recorded in the same examination room as the patients. However, for healthy people, severity assessment using the HAM-D was not conducted.

Table 2. Seventeen phrases used for recording

| No. | Phrase in Japanese | Purpose (meaning) |
|-----|--------------------|-------------------|

9
These voices were recorded by a pin microphone ME52W (OLYMPUS, Tokyo, Japan) attached to the chest about 15 cm from participants’ mouth. The recording device used was Portable Recorder R-26 (Roland, Shizuoka, Japan). Table 3 shows participants’ information for algorithm verification. The number of healthy individuals for verification and the number of their voice data were the same because
they were collected only once from each healthy participant. Regarding patients, some participants performed multiple data acquisitions. Seven, three, and one performed data acquisition twice, three, and four times, respectively. Data were acquired only once from the remaining 19 people. The recording format of the voices was linear PCM, the sampling frequency was 11025 Hz, and the number of quantization bits was 16 bits.

Table 3. Experimental participant information for algorithm verification

| Group          | Sex   | Number of participants | Mean age    | Number of data |
|----------------|-------|------------------------|-------------|----------------|
| Healthy        | Male  | 10                     | 42.7 ± 6.0  | 10             |
|                | Female| 4                      | 35.0 ± 14.4 | 4              |
| Major depression | Male  | 19                     | 43.7 ± 11.0 | 34             |
|                | Female| 11                     | 53.9 ± 8.2  | 12             |

Voice Emotion Analysis System

We used software ST Ver. 3.0 (AGI Inc., Tokyo, Japan) [25-27] to extract emotions from participants’ voice. The categories of emotional elements detected by ST software are: “anger,” “joy,” “sorrow,” “calmness” and “excitement.” The strength of each emotion is represented as an integer value from 0 to 10. A value of 0 means that the input speech does not contain the emotion at all. A value of 10 means that the input speech contains the emotion most strongly. The unit of speech emotion analysis by ST software is “utterance.” This is a part of continuous voice divided by breath. When a silent state changes to a speech state, it is considered that an utterance has started. When
the speech state continues for a certain period and changes to silence, it is considered
that the utterance has ended. Whether the silent state or the speech state is determined
from the volume using the threshold. The threshold was adjusted manually for each
recording, as the volume of the audio is affected by the participant and the condition of
the recording.

Algorithm

Vitality and Mental Activity

We proposed two scales—vitality and mental activity—as indices for the
degree of mental health obtained through voice analysis. Generally, “vitality” can be
defined in diverse ways; however, here, vitality refers to a scale that measures low for
patients with illnesses such as depression and high for healthy people. The main
difference between vitality and mental activity is the duration of the measurement.
Vitality is calculated from the emotional components of voice (calm, anger, joy, sorrow,
and excitement) based on short-term voice data such as a single phone conversation or a
hospital visit.

On the other hand, mental activity is calculated based on vitality data
accumulated over a certain period. Vitality changes based on the conditions at the time
of measurement in the same manner that blood pressure changes between post workout
and at rest. As accurate identification of high blood pressure is possible through long-
term monitoring, in this study, we aimed to accurately assess mental health by
introducing mental activity.

*Vivacity and Relaxation*

To calculate vitality, we introduced two new indices: “relaxation” and “vivacity.” To define these indices, we used four out of five indices output by ST: calmness, joy, sorrow, and excitement.

The fifth edition of the Diagnostic and Statistical Manual of Mental Disorders describes the characteristics of a major depressive episode as a continuing depressive state with loss of interests and happiness and feeling sorrow and emptiness [29]. In contrast, if there is a component of joy more relative to sorrow in emotion, it is considered a good mental state. Consequently, vivacity for an utterance was defined as follows:

$$Vivacity = \frac{Joy}{Joy + Sorrow}$$  \hspace{1cm} (1)

Stress and tension are major factors in mental health disorders. On the other hand, the relaxed state is mentally positive; thus, relaxation for an utterance was defined as follows:

$$Relaxation = \frac{Calm}{Calm + Excitement}$$  \hspace{1cm} (2)
In other words, relaxation increases with the increasing calmness component of emotion and decreasing excitement. Each emotional value output by ST, as well as the excitement, are expressed with integers in the range of 0–10. Therefore, vivacity and relaxation become real numbers in the range of 0.0–1.0. Vivacity and relaxation as defined above were calculated for each utterance. Below, we define vivacity and relaxation for an acquired voice as the mean value for each utterance contained in the acquired voice.

**Vitality Calculation Algorithm**

Vitality was calculated as the weighted mean of vivacity and relaxation defined in the previous section. Fig. 1 shows a scatter plot of relaxation and vivacity as calculated from data for the algorithm preparation.

![Fig. 1. Scatter plot of relaxation and vivacity. × and □ show the data of the healthy and patient groups for algorithm preparation. The straight line represents 0.60x + 0.40y = 0.52. The symbol × in the figure represents the data of the healthy group, while □ represents the data of the patient group. Data are plotted for each voice acquisition. There are 245]
data for the 13 people in the healthy group, and 58 for the 9 people in the patient group. We added a straight line that separates the healthy group from the patient group ($0.60X + 0.40Y = 0.52$). Based on this line, the vitality for each acquired voice was defined as follows:

$$V_{Vitality} = 0.60 \times Vivacity + 0.40 \times Relaxation$$ (3)

**Mental Activity Calculation Algorithm**

Vitality was calculated from short-term voice data such as a single examination or consultation. Therefore, depending on participants’ current mood, even healthy people might score low in vitality, while patients may score high. To compensate for such a weakness, mental activity was calculated from long-term trends in vitality. Specifically, to express long-term trend in vitality, we calculated the mean of accumulated vitality ($V_{Vitality}$).

Furthermore, when vitality has little fluctuation and is stagnant at low values, it is determined to have low mental activity. To actualize such a determination, we introduce a new index: standard deviation ($V_{VitalitySD}$) that expresses variations in vitalities for utterances contained in acquired voice. Then, the mean of vitality standard deviation of the accumulated acquired voice ($V_{VitalitySD}$) was calculated.
Fig. 2. Scatter plot of mean vitality and the mean (standard deviation) of vitality for each participant. × and □ indicate data for the healthy group and the patient group, respectively. The straight line represents $0.75x + 0.25y = 0.426$.

Fig. 2 is a scatter plot of the mean vitality and mean standard deviation of vitality for each participant calculated from the data for the algorithm preparation. The number of data plotted were 13 people for the healthy group and 9 people for the patient group (N = 22). When calculating the mean, we used all acquired voice data. In the figure, we added a straight line that separates the healthy group and the patient group ($0.75X + 0.25Y = 0.426$). Based on this line and using the mean and standard deviation of vitality, we define mental activity as follows:

$$MindActivity = 0.75 \times \overline{Vitality} + 0.25 \times \overline{VitalitySD}$$

Method of Analysis

According to the definition of Zimmerman and colleagues [30], the data of the patient group were divided into 3 groups by HAM-D score: no depression ($\leq 7$), mild (8–16), and moderate or severe ($\geq 17$).
The vitality of the four groups (i.e., these three and the healthy group) were compared among each other. P-values from Tukey-Kramer tests, the area under the curve (AUC) against Receiver Operating Characteristic (ROC), sensitivity, and specificity were used to evaluate the classification accuracy of Vitality.

Results

HAM-D score

The mean values of HAM-D score in each group are shown in Table 4. In addition, the mild group and the moderate or severe group will be collectively referred to as the depression group (HAM-D score ≥ 8). The mean HAM-D score for the depression group was 16.1 ± 7.4 (n = 22). The number of participants in each group was 11 men and 8 women in the no depression group and 5 men and 3 women in the mild group. All three participants in the moderate or severe group were men.

Table 4. Average value of HAM-D score for each group

| Group                  | Number of participants | Number of data | HAM-D score |
|------------------------|------------------------|----------------|-------------|
| No depression (HAM-D ≤ 7) | 19                     | 24             | 3.1 ± 2.3   |
| Mild (HAM-D = 8–16)    | 8                      | 13             | 11.5 ± 3.2  |
| Moderate or severe     | 3                      | 9              | 22.8 ± 6.6  |
Performance evaluation of vitality

We evaluated the performance of vitality using the data for algorithm verification shown in Table 3. Fig. 3 shows the relationship between HAM-D score and vitality for 46 data obtained from the patient group. There was a significant negative correlation between the two ($r = -0.33, n = 46, p < .05$).

Fig. 3. Relationship between HAM-D score and vitality in the data of patient group for algorithm verification.

Fig. 4. Comparison of vitality for each group. (a) represents data distribution of a healthy group, the no depression group, and the depression group. (b) shows the data distribution when the depression group is divided into the mild group and the moderate or severe group.

Fig 4 shows the distribution of vitality scores of the healthy group, the no depression group, the mild group, the moderate or severe group, and the depression group.
The mean vitality in each group was 0.60 ± 0.10 (n = 14), 0.55 ± 0.10 (n = 24), 0.51 ± 0.13 (n = 13), 0.47 ± 0.07 (n = 9), and 0.49 ± 0.11 (n = 22), respectively. The Tukey-Kramer test revealed significant differences between the healthy group and the depression group, and between the healthy group and the moderate or severe group (Ps = .0085 and .020, respectively). We used statistical analysis software R [31].

Next, to evaluate the discrimination performance of vitality, the area under the curve (AUC) of the receiver operating characteristic (ROC) curve, the sensitivity, and the specificity were used. Figure 5 shows the ROC curves when using vitality to identify whether the data for verification is for the healthy group or for each patient group. Here, the horizontal axis represents 1-specificity (false positive rate), and the vertical axis represents sensitivity (positive rate).

Fig. 5. Receiver operating characteristic curves when using vitality to identify groups

Table 5 shows the performance when the data of the healthy group and each group were distinguished using vitality. The AUC was 0.87, and the sensitivity and
specificity were 0.78 and 0.86, respectively regarding the discrimination performance between the healthy group and the moderate or severe group. On the other hand, both AUC were less than 0.7 regarding discrimination performance between the healthy group and the no depression group or mild group.

Table 5. Discrimination ability of vitality

| Group                | AUC  | Sensitivity | Specificity |
|----------------------|------|-------------|-------------|
| Health–Depression    | 0.76 | 0.55        | 0.93        |
| Health–Moderate or severe | 0.87 | 0.78        | 0.86        |
| Health–Mild          | 0.69 | 0.46        | 0.93        |
| Health–No depression | 0.64 | 0.80        | 0.50        |

AUC: area under the curve of the receiver operating characteristic curve.

Discussion

In this study, we developed a method to measure mental health using emotional components contained in voice. Two indicators were proposed: vitality based on short-term voice data and mental activity calculated from long-term voice data. As shown in Fig 3, there was a significant negative correlation between vitality and HAM-D score (i.e., depression severity assessed by a physician). In addition, as shown in Fig. 4, the group with a higher severity of depression tended to have a lower mean vitality.

There was a significant difference between the healthy group and the depression group, and between the healthy group and the moderate or severe group in
vitality. On the other hand, there was no significant difference between the healthy
group and the no depression group with almost no depressive symptoms, even if they
were outpatients with depression. This suggests the possibility of measuring treatment
effects by vitality (i.e., voice). Moreover, as shown in Fig. 5 and Table 5, the voice data
of the healthy group and the voice data of the moderate or severe group could be
identified with high accuracy using vitality. This suggests the possibility of screening
for severe depression in individuals by using voice.

In our other study, we verified vitality with Romanian and Russian native
speakers [32]. In this verification, BDI tests were conducted simultaneously with voice
recordings. There was a significant difference between the mean vitality of the
depression high-risk group (BDI scores ≥ 17) and the mean vitality of the depression
low-risk group (BDI scores < 17; p < .05). Specifically, the scores for question 9—
concerning suicidal ideation—took a value that ranged 0–3. There was a significant
difference between the mean vitality of the suicide low-risk group (0 or 1 points) and
the mean vitality of the suicide high-risk group (2 or 3 points; p < .01). In the future, we
will examine the vitality of native speakers of other languages, such as English.

As a limitation of this research, only the fixed phrase read-out speech was used
for verification. To apply vitality to free speech such as a call, further verification is
required. Furthermore, in the verification data, the number of voices collected for each participant, the sex ratio, and the age were not unified between groups. These differences may be reflected in the features of voice. For example, all participants in the moderate or severe group were men, and the number of participants was as small as three. In the future, it is necessary to acquire a lot of voices of female patients, especially those with severe depression, and to evaluate the performance level of vitality.

Further, mental activity was not validated because continuous data could not be collected sufficiently for the same participants in both the healthy group and the patient group. However, comparing Figs. 1 and 2 showing data for algorithm preparation, there is a possibility that mental activity can more accurately identify the data as compared to vitality, which will be addressed in the future.

Vitality and the mental activity can be measured by only voice, and their advantages are that they are non-invasive and less expensive as compared to self-administered tests such as the GHQ-30 and BDI and stress-check methods using saliva and blood. Moreover, it is also possible to record day-to-day state changes easily by implementing them on a smartphone or the like.
We developed a smart phone application that implemented the algorithm for vitality and mental activity—the Mind Monitoring System (MIMOSYS). We are currently conducting world-wide demonstration experiments using the MIMOSYS [33]. In the future, we plan to verify the effectiveness of vitality and mental activity with such large-scale data.

Conclusions

In this study, we developed a method to measure mental health from voice. The algorithm to estimate stress through emotion instead of analyzing stress directly from voice data is novel. The MIMOSYS implemented the algorithm for vitality and mental activity, which is a cost-effective and convenient measurement device. If the correlation between HAM-D score and vitality can be further enhanced, it may be used to aid doctors’ diagnoses in the future. By daily monitoring of vitality and mental activity using the MIMOSYS, we can encourage hospital visits for people before they become depressed or during the early stages of depression. This may lead to reduced economic loss due to treatment costs and interference with work.

List of abbreviations

MIMOSYS: Mind Monitoring System
GHQ: General Health Questionnaire

BDI: Beck Depression Inventory

HAM-D: Hamilton Rating Scale for Depression

ST: sensibility technology

ROC: receiver operating characteristic

AUC: area under the curve

Declarations

Ethics approval and consent to participate

Ethical approval was obtained from the National Defense Medical Collage Ethics Committee (no. 2248) and the Kitahara Rehabilitation Hospital Ethics Committee (no. 3).

Consent for publication

Not applicable.

Availability of data and material

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Competing interests
The authors declare that they have no competing interests.

**Funding**

This research was supported by the Center of Innovation Program from the Japan Science and Technology Agency and by JSPS KAKENHI [grant numbers JP16K01408 and JP15H03002]. The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript.

**Authors’ contributions**

S. T. was responsible for the design of the clinical study. A. Y., H. T., T. S., and M. T. were responsible for the execution of the clinical study including patient recruitment and retention and data collection. S. S. conceived the algorithm, analyzed data, and wrote the manuscript. M. N., Y. O., N. H., S. M., and S. T. contributed to the interpretation of study findings. All authors participated in the editing and revision of the final version of the manuscript.

**Acknowledgements**

We thank Dr. Shinsuke Kondo for assistance with data collection and all participants for participating. We also thank Editage [http://www.editage.com] for English-language editing.
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