Research report

Potential of a smartphone as a stress-free sensor of daily human behaviour

**Koki Mimura^a, Hirohisa Kishino^b, Genta Karino^a, Etsuko Nitta^{a,d}, Aya Senoo^{a,c},
Kentaro Ikegami^a, Tetsuya Kunikata^c, Hideo Yamanouchi^c, Shun Nakamura^{a,d}, Kan
Sato^a, Mamiko Koshiba^{a,c,d*}**

^aTokyo University of Agriculture and Technology, Tokyo, Japan

^bThe University of Tokyo, Tokyo, Japan

^cSaitama Medical University, Saitama, Japan

^dThe National Center of Neurology and Psychiatry, Tokyo, Japan

***Corresponding author**

Mamiko Koshiba

Saitama Medical University

38 Morohongo, Moroyama-cho, Iruma-gun, Saitama 350-0495, Japan

Tel +049-276-1232; Fax +049-276-1283; E-mail koshiba@saitama-med.ac.jp

Abbreviations

PCA: principal component analysis

Stdv: standard deviation

FFT: fast Fourier transform

LMM: linear mixed model

Abstract

Behaviour is one of the most powerful objective signals that connotes psychological functions regulated by neuronal network systems. This study searched for simple behaviours using smartphone sensors with three axes for measuring acceleration, angular speed and direction. We used quantitative analytic methodology of pattern recognition for work contexts, individual workers and seasonal effects in our own longitudinally recorded data. Our 13 laboratory members were involved in the care of common marmosets and domestic chicks, which lived in separate rooms. They attached a smartphone to their front waist-belts during feeding and cleaning in five care tasks. Behavioural characteristics such as speed, acceleration and azimuth, pitch, and roll angles were monitored. Afterwards, participants noted subjective scores of warmth sensation and work efficiency. The multivariate time series data were characterized by the subjective scores and environmental factors such as room temperature, season, and humidity, using the linear mixed model. In contrast to high-precision but stress-inducing sensors, the mobile sensors measuring daily behaviours allowed us to quantify the effects of the psychological states and environmental factors on the behavioural traits.

Keywords: Accelerometer, Gyroscope, Geomagnetic sensor, Thermal psychology, Seasonal modulation, Work efficiency

1. Introduction

It is generally expected that work efficiency is affected by an individual's psychobiological state and environmental factors. The psychological state of a subject (e.g., positive and negative emotions) may be reflected by whole-body cellular activity. Psychological dynamics cannot be reported in words, which have no basis for quantification or repeatability. However, behavioural signals could be used in detecting psychological factors, as has been revealed for neuronal network mechanisms in neuroscience. We have employed a multivariate analytic methodology of behavioural output analysis for quantitative emotional state translation called 'Bouquet', with multiple factors being measured from video images and sounds of humans and model animals [1–11]. Non-contact sensors such as video cameras are suited to psychological detection because they do not introduce artefacts of stress through attachment. However, they are limited in terms of their quality and quantity of detection. Instead, lighter and miniaturized contact mobile sensors might satisfy demand for behavioural detection, for instance, in wild animal studies [12–16]. Human motion has become easily detectable because of our adaptation to carrying mobile information terminals containing digital sensors and the development of signal processing with statistical mathematics [17–20]. We preliminarily evaluated the potential of employing mobile behavioural sensing systems used in everyday life for psychological quantification before clinical application in neuropsychiatric treatment. Subjects completed a simple questionnaire on subjectively self-reported psychological states of ambient sensation and work efficiency immediately after they completed each of five routine tasks of taking care of animals. The results were then screened using effective information processing with assessment of the psychological states and environment factors through multivariate correlation. It is known that complex physical motion patterns associated with multiple neuronal networks are affected by psychological states through sensory inputs and neuronal cognition processes. Such responsible neuronal

networks, which are innervated and developed with a memorized function after neuromolecular and physiological mechanism experiences, have been studied [21, 22]. The current study reports on the potential utility of smartphones embedded with accelerometers as tools for the long-term real-time monitoring of human behaviour. Although the number of participants in this study was limited, it was possible to quantify the effects of self-reported psychological indices and environmental factors on behavioural indices. The monitoring system does not induce stress and is inexpensive, and may thus become a powerful tool for large-scale behavioural studies.

2. Materials and Methods

2.1. Participants and rooms

The study protocol was approved by the ethics review committee of Tokyo University of Agriculture and Technology (TUAT (22-11)). Behavioural data were collected with the written informed consent of all participants. The results and their analysis were explained to the participants, who agreed that the results could be published.

Thirteen healthy adult participants (seven males aged 23.7 ± 2.1 years and six females aged 27.7 ± 9.7 years; Table 1) carried out self-recordings from September 27 to October 13 and from November 13 to December 3, 2012.

Table 1

ID	Gender	Age	Days (September - October)					Days (November - December)				
			task1	task2	task 3	task 4	task 5	task 1	task 2	task 3	task 4	task 5
1	F	26	2	3	3	4	3	6	2	5	3	3
2	F	26	2	4	3	2	1	2	6	3	5	3
3	F	23	4	5	2	3	5	4	1	4	3	3
4	F	23	1	2	1	4	3	2	11	2	7	8
5	F	21	1	0	1	0	1	7	0	6	4	2
6	F	47	0	4	1	1	3	3	4	3	1	2
7	M	27	0	3	1	2	3	3	5	4	3	2
8	M	23	0	2	0	1	1	1	4	2	2	2
9	M	21	0	1	4	3	1	3	5	2	1	5
10	M	25	2	1	4	3	2	1	5	4	3	3
11	M	23	2	2	2	1	4	5	3	5	0	7
12	M	22	2	2	3	2	5	3	2	2	1	1
13	M	26	2	3	4	3	3	1	7	1	4	5

Table 1: Number of recorded days for each participant

Data were collected as participants performed daily care tasks from 9:00 am to 10:00 am in the animal breeding rooms of TUAT, where the temperature was controlled to around 26 °C.

The care tasks were to take care of paired juvenile common marmosets (task 1, room size: width $\times$ depth $\times$ height = 1 m $\times$ 0.9 m $\times$ 2.4 m), single juvenile marmosets (task 2, 0.8 m $\times$ 0.9 m $\times$ 2.4m), adult marmosets (task 3, 1.8 m $\times$ 2.7 m $\times$ 2.2 m), domestic chicks (task 4, 1.8 m $\times$ 1.8 m $\times$ 2.2m), and other tasks such as washing (task 5, 1.6 m $\times$ 0.7 m $\times$ 2.4m).

However, in some cases, the order of tasks and sharing of tasks were changed to increase the efficiency of the participants' work.

2.2. Data collection

Behavioural data were obtained using the built-in sensors of Docomo NEXT Series GALAXY S II SC-02C smartphones (SGH-N033, NTT Docomo, Japan) attached to the front waist (Fig. 1c). Data were stored in the smartphone using a custom-made Java application (NTT Software, Japan). We recorded three types of physical data: data for the three axes of accelerometer, data for the three axes of the gyroscope, and data for the roll, pitch, and azimuth (Fig. 1c). The time resolution in recording all data was 0.2 s (i.e., the sampling rate was 5 Hz). To justify the use of the smartphone's sensors, data collected for four healthy adult volunteers (one female and three males) were compared with data simultaneously recorded by research-grade accelerometers (TSND121, ATR-Promotions, Japan) attached to the smartphone. These accelerometers had a maximum time resolution frequency of 1000 Hz, resolution of acceleration of 0.12 mili G (gravity), and resolution of angular velocity of 0.15 degrees per second. The ambient temperature and humidity were measured every 5 minutes using a wireless logger (MD-logger, CHINO, Japan). Subjective psychological scores for Warmth Sensation (3: warm, 2: medium, and 1: cool) and Work Efficiency (3: high, 2: medium, and 1: low) were reported in a questionnaire immediately after each task. The outdoor temperature at 9 a.m. for the city of Fuchu in Tokyo was obtained each morning from the website of the Japan Meteorological Agency [23].

2.3. Measurement of behavioural and psychological indices, and environmental factors

Mean values and standard deviations of each factor over periods of 30 s measured by smartphone sensors were obtained (Items 1–18 listed in Table 2). The sensor of azimuth

(Item 4 in Table 2) was measured each deference per 0.2 second, consequently, if a participant stands vertically, the value of Azimuth means the angular speed of AnX (Item 7). Ambient temperature (Item 28) and relative humidity (Item 29) were adjusted every 30 s to match the time scale of the smartphone sensors. Subjective scores of Warmth Sensation (Item 30) and Work Efficiency (Item 31) were kept the same value per contextual work. Following our preliminary estimation of the participants' periodic behaviours in intervals of 30 s, the current frequency analyses of behavioural factors (Items 19–27) employed a 600-s moving-window fast Fourier transform (FFT) in R software [23, 24]. The time window was shifted in steps of 30 s.

The calculated results are presented as frequency–time spectrograms. After preliminary evaluation for the frequency range of 1/600–5 Hz and seeking correlation to other factors, we decided to use low- and high-pass filtering and extracted behavioural components of 30–100 s cycle with amplitude squareds.

2.4. Characterization of behavioural indices employing the linear mixed model (LMM)

We characterized the 35 behavioural indices using the LMM and R package lme4 [24, 25]. We regressed each of the behavioural indices using the psychological indices and environmental factors. We allowed the between-individual variability of the regression coefficients to remain as random effects:

$$\text{Behavioral Factor} \sim \text{Work Efficiency} + \text{Warm Sensation} + \text{temperature} + \text{humidity} + \text{day} + (\text{Work Efficiency} + \text{Warm Sensation} + \text{temperature} + \text{humidity} + \text{day} | ID)$$

. To interpret the result, we applied principal component analysis (PCA) with a variance–covariance matrix to the t-values of the fixed effects.

Table 2

Factors				Contents
mean value of	1	AcX	m/sec^2	the acceleration (Ac) on the X-axis (Vertical)

behavioural factors for 30sec	2	AcY	m/sec^2	the acceleration on the Y-axis (Lateral)
	3	AcZ	m/sec^2	the acceleration on the Z-axis (Forward-Backward)
	4	Azimuth	degree/sec	the angular speed of azimuth angle
	5	Pitch	degree	the pitch angle
	6	Roll	degree	the roll angle
	7	AngX	radian/sec	the angular speed around the X-axis (Vertical)
	8	AngY	radian/sec	the angular speed around the Y-axis (Lateral)
	9	AngZ	radian/sec	the angular speed around the Z-axis (Forward-Backward)
standard deviation of behavioural factors for 30sec	10	AcX.sd		standard deviation(sd) of Ac_X (Vertical)
	11	AcY.sd		sd of Ac_Y (Lateral)
	12	AcZ.sd		sd of Ac_Z (Forward-Backward)
	13	Azim.sd		sd of Azim
	14	Pitch.sd		sd of Pitch
	15	Roll.sd		sd of Roll
	16	AngX.sd		sd of Ang_X (Vertical)
	17	AngY.sd		sd of Ang_Y (Lateral)
cycle components of behavioural factor	18	AngZ.sd		sd of Ang_Z (Forward-Backward)
	19	AcX.fft		30-100sec cycle component of Ac_X, square of amplitude
	20	AcY.fft		30-100sec cycle component of Ac_Y, square of amplitude
	21	AcZ.fft		30-100sec cycle component of Ac_Z, square of amplitude
	22	Azim.fft		30-100sec cycle component of Azim, square of amplitude
	23	Pitch.fft		30-100sec cycle component of Pitch, square of amplitude
	24	Roll.fft		30-100sec cycle component of Roll, square of amplitude
	25	AngX.fft		30-100sec cycle component of Ang_X, square of amplitude
	26	AngY.fft		30-100sec cycle component of Ang_Y, square of amplitude
environmental factors	27	AngZ.fft		30-100sec cycle component of Ang_Z, square of amplitude
	28	temperature	Degree Celsius	ambient temperature
subjective score	29	humidity	%	relative humidity
	30	Warm		Warmth Sensation (1=cool, 2=medium, 3=warm)
	31	Eff		Work Efficiency (1=low, 2=medium, 3=high)

Table 2: Factors considered in PCA.

3. Results

3.1. Preliminary justification of a smartphone's ability to sense human motion

Because the sensing frequency of a smartphone (5 Hz) is not considered high, we preliminary justified the sensing ability of a smartphone by comparing the results obtained with a smartphone with the results obtained with accelerators having higher precision for simple optimized motion activity in each sensor direction (Fig. 2). According to our initial analysis of smartphone data (the averaging of 5-Hz signals over 30 seconds), all participants were asked to complete four pre-planned 1/30-Hz periodic motions that involved squatting and standing vertically (corresponding to Items 1, 10, and 19 in Table 2), lunging left and right laterally (Items 2, 11, and 20), rotating horizontally clockwise and counterclockwise (Items 8, 17, and 26), and tilting left and right laterally (Items 9, 18, and 27). The raw signals of two synchronized sensors (one being a smartphone detector and the other a high-precision detector) were collected at 5 Hz for 600 seconds (trend graphs of Fig. 2) and were post-analysed as the squared intensity of the frequency component employing an FFT density spectrogram of 600-s window, the cycle versus time, similarly to the unit of 600 s in the following experiments. A series of comparisons for four healthy adults resulted in a smaller amplitude of the trend waves when using a smartphone instead of a research-grade sensor, but certain periodic waves were similarly identified for all participants. Dense bands in the FFT spectrograms for a cycle of 30 s were together confirmed consistently, except for a smear-like band at a cycle of 30 s and a harmonic-like at a cycle of 60 s for the smartphone sensor of laterally tilting motion (Fig. 2D). According to these preliminary justifications, we employed band-pass filtering to accept only frequencies within 1/30–1/100 Hz in recording human motion signals using smartphone sensors.

3.2. Example dataset obtained from raw-signal trends of a smartphone sensors and power spectrograms of the FFT analysis in longitudinal acquisition

Smartphones with built-in sensors were used to acquire a set of participant motions during animal-care tasks. An example set of eight trends for a participant acquired using smartphone sensors at the waist during three task contexts 1 to 3 (Fig. 1b) are shown in Fig. 3A–C except for data of four cardinal directions (data not shown). We then reviewed all participants’ graphs and the preliminary analysis of Fig. 2. We filtered out the lower (1/100–1/300 Hz) and higher (1/5–1/30 Hz) bands and extracted signals between 1/30–1/100 Hz (Fig. 2, black bands on the vertical axes) as a typical FFT band to avoid the risk of including FFT artefacts.

Table 3: The t-values of the fixed effects estimated using an LMM with random effects of between-individual variability

	Factor	Efficiency	Heat	Temperature	Humidity	Day	(Intercept)
1	AcX	-0.549	0.457	-0.003	-1.050	0.157	0.054
2	AcY	2.334	-0.822	1.078	0.887	0.805	-1.285
3	AcZ	0.642	0.806	-0.068	1.300	-0.013	-7.448
4	Azimuth	-2.463	-1.873	-1.913	-0.339	-1.956	3.401
5	Pitch	-0.158	-0.878	1.025	0.072	0.416	-0.885
6	Roll	-0.718	0.383	0.079	-1.397	-0.008	0.050
7	AngX	1.690	0.758	0.008	-1.623	-1.556	0.554
8	AngY	-0.598	1.345	-0.618	0.775	-0.352	0.483
9	AngZ	0.131	-0.425	-0.761	0.999	-0.899	0.763
10	AcX.sd	-0.185	0.423	0.196	-0.121	-0.730	0.052
11	AcY.sd	1.052	-0.414	-1.888	0.214	-2.384	2.497
12	AcZ.sd	-0.326	0.525	0.307	-0.699	-0.869	0.048
13	Azim.sd	1.190	0.621	0.820	-2.066	-1.113	-0.329
14	Pitch.sd	0.554	0.169	-0.506	0.029	-0.456	0.470
15	Roll.sd	-0.065	0.532	1.284	-1.250	-0.026	-0.915
16	AngX.sd	0.928	-0.663	1.638	-2.225	-0.289	-1.122
17	AngY.sd	0.138	1.376	-1.531	-0.051	-2.527	2.349
18	AngZ.sd	-0.588	-0.253	1.578	-0.059	0.092	-1.592
19	AcX.fft	-0.680	0.996	-0.467	1.435	-1.069	1.810
20	AcY.fft	-0.013	0.058	1.717	-0.192	0.560	-1.538
21	AcZ.fft	2.451	1.270	-2.136	1.215	-1.577	1.438

22	Azim.fft	0.068	-0.264	-0.104	0.861	1.262	-3.342
23	Pitch.fft	0.182	-0.094	-0.806	0.350	-0.640	0.766
24	Roll.fft	-1.359	1.019	-1.130	1.208	-1.235	6.494
25	AngX.fft	-0.597	-1.018	-0.631	0.783	0.792	-0.234
26	AngY.fft	-0.734	-1.189	-2.142	1.181	0.500	5.835
27	AngZ.fft	-1.002	-2.952	-0.361	2.187	0.008	0.254

Table 3.

A t-value whose absolute value was more than 2 was determined to be significant. Black and grey cells in Table 3 highlight absolute values greater than 2.

3.3. Effects of psychological and environmental factors on the behavioural indices

Work Efficiency affects lateral acceleration (Item 2 in Table 3) and the 30–100-s cycle component of forward–backward acceleration (Item 21) positively, and the azimuth angular speed (Item 4) negatively (Table 3). Warmth Sensation affects only the cycle component of tilting acceleration (Item 27) negatively. Ambient temperature negatively affects two cycle components of forward–backward acceleration (Item 21) and bowing angular speed (Item 26). Ambient relative humidity positively affects the cycle component of tilting angular speed (Item 27), and negatively affects the standard deviation of the angular speed of azimuth (Item 13) and the rotation around the vertical axis of the body (Item 16). The seasonal effect between late summer and winter (day, the fifth factor column in Table 3) relates to the standard deviations of lateral shifting acceleration (Item 11) and bowing angular speed (Item 17). Reciprocal effects between two behavioural factors are seen for the cycle components of AcZ.fft (Item 21) and AngZ.fft (Item 27). This can be viewed as the behavioural factor AcZ.fft (Item 21) becoming active if Work Efficiency increases or ambient temperature

decreases. As Warmth Sensation decreases or relative humidity increases, the factor AngZ.fft (Item 27) seems to become active.

To interpret the correlated effects, we applied PCA to the t-values of Table 3. The cumulative proportion of the first three principal components was 84.3%, and that of the first four principal components was 95.7%. Figure 4A and B shows the scores and factor loadings of the first four principal components. The first principal component (PC 1) represents the effects of environmental factors: the positive effect of ambient temperature vs. the negative effect of relative humidity. The behavioural factors of standard deviation (Azimuth.sd (Item 13), Roll.sd (Item 15), and AngX.sd (Item 16)) corresponded to higher PC1 scores ($PC1 > 1.7$) (Fig. 4A), while the factors of cycle components (Roll.fft (Item 24), AngY.fft (Item 26), and AngZ.fft (Item 27)) corresponded to lower PC1 scores ($PC1 < -1.7$). PC2 revealed the positive effects of two psychological scores, Warmth Sensation and Work Efficiency, and the negative effect of the seasonal factor, day. Four behavioural factors, AngX (Item 7), AcY.sd (Item 11), AngY.sd (Item 17) and AcZ.fft (Item 21), corresponded to higher PC2 scores ($PC2 > 1.5$). In contrast, the three factors of Pitch (Item 5), AngX.fft (Item 25) and AngZ.fft (Item 27) corresponded to lower PC2 scores ($PC2 < -1.5$). In summary, the behavioural activity corresponding to higher Work Efficiency in spite of higher Warmth Sensation in summer was characterized as bending at the waist and rotating around the body axis, with a suppressed cycle component of shifting forward–backward and tilting laterally, simultaneously. PC3 represents negative effects of Work Efficiency and relative humidity on behavioural factors AcY (Item 2) and AcZ.fft (Item 21) for lower PC3 scores and Azimuth (Item 4) for higher PC3 scores. This indicates that the participant group tended to perform much lateral motion with 1/30-Hz forward–backward periodic motion but suppressed horizontal rotation for high Work Efficiency in a highly humid environment. PC4 features negative correlation between Warmth Sensation or Work Efficiency and AngY (Item 8), AcX.fft (Item 19), and Roll.fft

(Item 24) in the case of a high score ($PC4 > 1.3$) or AcY.sd (Item 11) in the case of a low score ($PC4 < -1.3$). PC3 and PC4 seem to be affected less by the seasonal effect, day.

4. Discussion

4.1. Possibility of multi-domain interactive processing of behavioural signals acquired by everyday stress-free mobile sensors for neuropsychological studies

The highly advanced recording of neuronal signals associated with psychological behaviour plays a central role in furthering our understanding of psychiatry. To make such recordings, we suggested the possibility of a method of daily assessment employing a smartphone and multi-domain data analysis.

It is important that data are not only precise and accurate but that we can acquire longitudinal data in a stress-free manner. Compared with research-grade accelerometers, general-use smartphones with a built-in accelerometer, gyroscope and geomagnetic sensors are considered to have poor precision and accuracy. This was shown by the small difference in results for the two types of devices in our preliminary test (Fig. 2), but the smartphone was suited to acquiring daily data and volunteer participants wearing the smartphone made no complaints when filling out the questionnaire after completing each task. Participants were laboratory students, all of whom were familiar with the use of their own similar smartphones in their daily lives. The activities of animal care that the participants carried out every morning were their usual work as part of their own studies on animal development, and were not designed for the current study. Three of the 13 participants were new members of the laboratory and unfamiliar with the scope of the laboratory research. They had learnt tasks of animal care for more than half a year before the recording started but were regarded as outside subjects. However, in future study, appropriate subject selection should involve

training subjects enrolled outside the laboratory to perform the tasks of the study. This would avoid the risk of self-experimenter bias. Although we did not design a signal processing method before we acquired our unfamiliar mass recording of data, we attempted to select common methods of analysis involving averaging, smoothing, standard deviations, frequency analysis, and the FFT, and then to find a suitable multivariate analysis for the data employing the LMM and PCA, to visualise the complex high- and low-order of the correlated structure of behaviour, psychology and environment. It is supposed that such longitudinal data recorded in a normal laboratory would involve little interfusion of arbitrariness. For the main approach of multi-domain interactive processing to extrapolate the complex structure of neuropsychological mechanisms through behavioural multivariate correlation and its dynamics, we integrated multiple effects employing the LMM to consider inter- and intra-individual variability and then PCA to visualise the multi-parametric structure; relevant behavioural motion variables thus emerged. This signal processing will possibly determine certain working motion characteristics and support the quantitative recognition of highly complex behaviours and environment-dependent psychological states with frequency, multivariate and longitudinal correlation analyses. The integrated results of Fig. 4 reveal that, when considering both psychological scores, Warmth Sensation and Work Efficiency are high in summer because of the negative direction of the 'day' arrow, the common behavioural character was supposed as the horizontal rotation activity (Factor 7 in Table 2) high and the periodic lateral tilting activity around 1/30–1/100 Hz (Factor 27 in Table 2) low in the PC1-2 plane although these general features were independent of ambient temperature and the PC3-4 plane revealed Warmth Sensation and Work Efficiency to be almost independent of each other. This complex correlation obtained by multivariate interactive analyses revealed that the scores of psychological factors that are normally supposed to be susceptible to ambient temperature were less relevant, and that there is a more prominent

effect of season and ambient humidity on the psychology of human behavioural and psychological mechanisms in terms of periodic motion such as more lateral tilting (AngZ.fft (27)) in the case of high humidity and low Warmth Sensation and Work Efficiency (Fig. 4A).

4.2. Discussion for neuropsychiatric studies

We confirmed the climate variation from late summer to early winter; i.e., the outside air temperature decreased gradually like the ambient temperature and relative humidity (Fig. 5). The observed analytic information presented in Fig. 4 appeared to differ from the seasonal shift because the day from August to December was positively correlated with increasing ambient temperature. This means the representative information must be resulted by the data-driven connotative matter. The important point in the current report was to show the subjective psychological dynamics affected by seasonal climate in a quantitative manner as supported by complex behaviours dynamics. Consequently, it was possible to identify the subject's feeling of warmth as clearly not absolute but relative to the seasonal environment, perhaps involving adaptation or accommodation regulated by the learning mechanism of neuronal circuits and linked to psychiatry as maladaptation [26, 27] over our lives. Our animal facility was isolated by four or five walls and doors from the outdoors and the ambient condition was constantly regulated such that the facility was continually warm for animal breeding, yet the facility was slightly affected by the outside climate. During seasonal modulation of the current study conditions, it had been preliminarily recognized that the subjective warm sensation tended to modulate from warm to cool as emotionally negative to positive as a result of wearing double-layer uniforms. In the situation of the current study, it was confirmed that the psychological scores of Warmth Sensation and Work Efficiency changed in parallel. These results inferred the possibility that psychological modulation might

be represented in these complex behavioural patterns as reported previously [1–11, 28] and suggested evaluation in human workers including simple shift, acceleration and several ten-second-order cyclic motion. The current study investigated whether the technology could represent not only the commonality but also the individuality that needs to be recognized in all psychological and psychiatric fields.

As homeothermic animals, humans have multiple thermal regulation systems of the body relating to the sympathetic and parasympathetic nervous systems, athrocytosis, metabolism, immunology, respiratory, shivering, diaphoresis, blood circulation, motor activities, endocrinology, epithelium, adipose and other cellular accumulation and resolution, and regulation [29–31]. As the process relevant to the current study, thermal environmental input from sensory organs of the whole body to the central nervous systems crucially affects our psychological state [32–34]. Furthermore, the acquired information of superior signals, our daily behaviour, would be linked to various smart service networks such as energy balancing for sustainability of animals and the Earth [37], which are both regulated by periodic mechanisms.

In relation to the biological synchronised waveform, not only a higher frequency of brain electroencephalographic rhythms but also a lower frequency less than 0.1 Hz has been discriminated; e.g., slow cortical potentials in normal volunteers [38] or slow periodic modulation in patients with Alzheimer's disease [39]. Functional magnetic resonance imaging with similar low-frequency blood-oxygen-level-dependent signal fluctuations during wakeful resting was also reported to reveal a difference in, for instance, sleep and consciousness that is supposed to be due to regulation in thalamocortical neuronal networks [40]. As for the cited studies, it is expected that animal model research will investigate the neuro-psychobiological mechanism of behavioural characterization we found.

The present study has reported a preliminary phase of investigation that is expected to be followed by further studies employing the developed simple detection and behavioural signal processing.

Conclusion

A general-use smartphone with built-in accelerometer, gyroscope and geomagnetic sensors possibly detected certain working motion characteristics among humans. Our signal processing involving frequency, multivariate and longitudinal correlation analyses might support the quantitative recognition of complex behaviours and environment-dependent psychological states. This application suggests a certain correlation between warmth sensation, work efficiency and complex motion patterns that implies the presence of a neuronal modulation system affected by specific environmental factors. The technology might visualize commonality with consideration of individual random effects in structured multivariate correlation.

Acknowledgements

We express our appreciation to Dr. Kenichiro Shimatani for his support in statistical mathematics. We also thank Dr. Yuka Shirakawa, Mr. Shimpei Ozawa, Ms. Saya Obara, Ms. Hitomi Sekihara, Mr. Yuta Fukushima, Mr. Takeshi Sagawa, and Ms. Natsuki Nojima of Tokyo University of Agriculture and Technology for their support. We thank Mr. Michael Luke Santamaria for his assistance in finalizing our manuscript. This work was supported mainly by JST-ALCA (2012-2013), and was partially supported by MEXT; JSPS KAKENHI

Grant Number 21200017, 25119509, 25282221; JSPS Research Fellow, DC2 -PD (2012–2014) in Japan.

References

- [1] Koshiha M, Mimura K, Sugiura Y, Okuya T, Senoo A, Ishibashi H, Nakamura S. Reading marmoset behavior 'semantics' under particular social context by multi-parameters correlation analysis, *Prog Neuro-Psychopharmacol & Biol Psychiatry* 2011;35:1499-504. doi: 10.1016/j.pnpbp.2011.01.021.
- [2] Senoo A, Okuya T, Sugiura Y, Mimura K, Honda Y, Tanaka I, Kodama T, Tokuno H, Yui K, Nakamura S, Usui S, Koshiha M. Effects of constant daylight exposure during early development on marmoset psychosocial behavior, *Prog Neuro-Psychopharmacol Biol Psychiatry* 2011;35:1493-8. doi: 10.1016/j.pnpbp.2011.01.008.
- [3] Mimura K, Mochizuki D, Nakamura S, Koshiha M. A sensitive period of peer-social learning. *J Clinical Toxicology* 2013; 3: 158.
- [4] Shirakawa Y, Mimura K, Senoo A, Fujii K, Shimizu T, Saga T, Tanaka I, Honda Y, Tokuno H, Usui S, Kodama T, Tsugawa W, Sode K, Nakamura S, Koshiha M. Multivariate correlation analysis suggested high ubiquinol and low ubiquinone in plasma promoted primate's social motivation and IR detected lower body temperature. *J Clinical Toxicology* 2013;3:2.
- [5] Koshiha K, Shirakawa Y, Mimura K, Senoo A, Karino G, Nakamura S. Familiarity perception call elicited under restricted sensory cues in peer-social interactions of the domestic chick. *Plos One* 2013;8(3): e58847.
- [6] Shirakawa Y, Nakamura S, Koshiha M. Peer-social network development revealed by brain multivariate correlation map with 10 monoamines and 11 behaviors. *J Clinical Toxicology*. 2013; 3: 161.

- [7] Mimura K, Shirakawa Y, Nakamura S, Koshiha K. Multivariate PCA analysis combined with Ward's clustering for verification of psychological characterization in visually and acoustically social contexts. *J Clinical Toxicology*. 2013;3:158.
- [8] Mimura K, Nakamura S, Koshiha K. A flexion period for attachment formation in isolated chicks to unfamiliar peers visualized in a developmental trajectory space through behavioral multivariate correlation analysis. *Neuroscience Letters* 2013;547:70-5
- [9] Koshiha M, Nakamura S, Mimura K, Senoo A, Karino G, Amemiya S, Miyaji S, Kunikata T, Yamanouchi H. Socio-emotional development evaluated by Behaviour Output analysis for Quantitative Emotional State Translation (BOUQUET): Towards early diagnosis of individuals with developmental disorders. *OA Autism* 2013;1(2):18.
- [10] Koshiha M, Karino G, Senoo A, Mimura K, Shirakawa Y, Fukushima Y, Obara S, Sekihara H, Ozawa S, Ikegami K, Ueda T, Yamanouchi H, Nakamura S. Peer attachment formation by systemic redox regulation with social training after a sensitive period. *Scientific Reports* 2013;3:2503.
- [11] Koshiha M, Senoo A, Mimura K, Shirakawa Y, Karino G, Obara S, Ozawa S, Sekihara H, Fukushima Y, Toyotoshi Ueda T, Kishino H, Tanaka T, Ishibashi H, Yamanouchi H, Yui K, Nakamura S. A cross-species socio-emotional behaviour development revealed by a multivariate analysis. *Scientific Reports* 2013;3:2630.
- [12] Cooke SJ, Hinch SG, Wikelski M, Andrews RD, Kuchel LJ, Wolcott TG, Butler PJ. Biotelemetry: a mechanistic approach to ecology, *TRENDS in Ecology and Evolution* 2004;19: 334-43.
- [13] Yoda K, Naito Y, Sato K, Takahashi A, Nishikawa J, Ropert-Coudert Y, Kurita M, Le Maho Y. A new technique for monitoring the behaviour of free-ranging Adélie penguins. *J Exp Biol* 2001;204(Pt 4):685-90.

- [14] Sakamoto KQ, Sato K, Ishizuka M, Watanuki Y, Takahashi A, Daunt F, Wanless S., Can ethograms be automatically generated using body acceleration data from free-ranging birds? PLoS One 2009;4(4):e5379. doi: 10.1371/journal.pone.0005379. Epub 2009 Apr 30.
- [15] Nathan R, Spiegel O, Fortmann-Roe S, Harel R, Wikelski M, Getz WM., Using tri-axial acceleration data to identify behavioral modes of free-ranging animals: general concepts and tools illustrated for griffon vultures. Exp Biol 2012;215(Pt 6):986-96. doi: 10.1242/jeb.058602.
- [16] Wang N, Ambikairajah E, Lovell NH, Celler BG., Accelerometry based classification of walking patterns using time-frequency analysis. Conf Proc IEEE Eng Med Biol Soc 2007;2007:4899-902.
- [17] Lester J, Choudhury T, Borriello G. A Practical Approach to Recognizing Physical Activities., PERSASIVE'06 Proceedings of the 4th international conference on Pervasive Computing, 2006, p1-16, doi>10.1007/11748625_1.
- [18] Wu W, Dasgupta S, Ramirez EE, Peterson C, Norman GJ., Classification accuracies of physical activities using smartphone motion sensors. J Med Internet Res 2012;14(5):e130. doi: 10.2196/jmir.2208.
- [19] Joundi RA, Brittain JS, Jenkinson N, Green AL, Aziz T. Rapid tremor frequency assessment with the iPhone accelerometer. arkinsonism Relat Disord 2011;17(4):288-90. doi: 10.1016/j.parkreldis.2011.01.001. Epub 2011 Feb 5.
- [20] Donaire-Gonzalez D, de Nazelle A, Seto E, Mendez M, Nieuwenhuijsen MJ, Jerrett M., Comparison of physical activity measures using mobile phone-based CalFit and Actigraph. J Med Internet Res 2013;15(6):e111. doi: 10.2196/jmir.2470.
- [21] Cheung SS., Interconnections between thermal perception and exercise capacity in the heat. Scand J Med Sci Sports. 2010;20 Suppl 3:53-9. doi: 10.1111/j.1600-

- [22] Labunskay G, Meiri N.R-Ras3/(M-Ras) is involved in thermal adaptation in the critical period of thermal control establishment. *J Neurobiol.* 2006 Jan;66
- [23] The website of the Japan Meteorological Agency <http://www.data.jma.go.jp/obd/stats/etrn/>
- [24] Lee, Y., Nelder, J. A., and Pawitan, Y. (2006) Generalized linear models with random effects. Unified analysis via H-likelihood. Boca Raton, Chapman and Hall/CRC.
- [25] The R Project for Statistical Computing, <http://www.r-project.org/>
- [26] The International Classification of Diseases (ICD), World Health Organization. American Psychiatric Association.
- [27] DSM-V The Diagnostic and Statistical Manual of Mental Disorders (DSM), the American Psychiatric Association 2013
- [28] Kalueff AV, LaPorte JL, Murphy DL, Sufka K. Hybridizing behavioral models: a possible solution to some problems in neurophenotyping research? *Prog Neuropsychopharmacol Biol Psychiatry* 2008; 32:1172-1178. doi: 10.1016/j.pnpbp.2007.12.010.
- [29] Nakamura K. Central circuitries for body temperature regulation and fever. *Am J Physiol Regul Integr Comp Physiol* 2011;301(5):R1207-28. doi: 10.1152/ajpregu.00109.2011. Epub 2011 Sep 7.
- [30] Human RLB. Cardiovascular adjustments to exercise and thermal stress. *Physiol Rev* 1974.54(1):75-159. Review.
- [31] Poon CS. Optimal interaction of respiratory and thermal regulation at rest and during exercise: role of a serotonin-gated spinoparabrachial thermoafferent pathway. *Respi Physiol Neurobiol* 2009;169(3):234-42. doi: 10.1016/j.resp.2009.09.006. Epub 2009 Sep 19.

- [32] Hughes RA, Sufka KJ. The ontogeny of thermal nociception in domestic fowl: thermal stimulus intensity and isolation effects. *Dev Psychobiol.* 1990.Mar;23(2):129-40.
- [33] McGlone F, Reilly D. The cutaneous sensory system. *Neurosci Biobehav Rev* 2010;34(2):148-59. doi: 10.1016/j.neubiorev.2009.08.004. Epub 2009 Aug 25.
- [34] Roth TC 2nd, Gallagher CM, LaDage LD, Pravosudov W. Variation in brain regions associated with fear and learning in contrasting climates. *Brain Behav Evol* 2012;79(3):181-90. doi: 10.1159/000335421. Epub 2012 Jan 26.
- [35] Molendijk ML, Haffmans JP, Bus BA, Spinhoven P, Penninx BW, Prickaerts J, Oude Voshaar RC, Elzinga BM. Serum BDNF concentrations show strong seasonal variation and correlations with the amount of ambient sunlight. *PLoS One* 2012.7(11):e48046. doi: 10.1371/journal.pone.0048046. Epub 2012 Nov 2.
- [36] Comasco E, Sylvén SM, Papadopoulos FC, Orelund L, Sundström-Poromaa I, Skalkidou A. Postpartum depressive symptoms and the BDNF Val66Met functional polymorphism: effect of season of delivery. *Arch Womens Ment Health* 2011;14(6):453-63. doi: 10.1007/s00737-011-0239-x. Epub 2011 Oct 14.
- [37] Koshiba M, Senoa A, Karino G, Shirakawa Y, Mimura K, Sagawa T, Tsugawa Y, Sode K, Nakamura S, Blood Glucose Dependence on Emotional Behaviors and Body Surface Temperatures in Common Marmoset's Socio-Psychological Learning with Peers - for 'Development of Human-Environment Interface by Sensing and Multivariate Analysis of Bio-Ecosystem', *ECS Trans* 2013 .50 (28) 9-14, doi: 10.1149/05028.0009ecst
- [38] Novák P1, Lepicovská V. Increase of slow periodic modulation of EEG in a patient with Alzheimer's disease. *Physiol Res.* 1992;41(4):293-7.
- [39]. Garipelli G1, Chavarriaga R, Millán Jdel R, Single trial analysis of slow cortical potentials: a study on anticipation related potentials., *J Neural Eng.* 2013 Jun;10(3):036014. doi: 10.1088/1741-2560/10/3/036014. Epub 2013 Apr 23.

[40] Spoormaker VI1, Schröter MS, Gleiser PM, Andrade KC, Dresler M, Wehrle R, Sämann PG, Czisch M. Development of a large-scale functional brain network during human non-rapid eye movement sleep. *J Neurosci*. 2010 Aug 25;30(34):11379-87. doi: 10.1523/JNEUROSCI.2015-10.2010.

Figure captions

Fig. 1. Working conditions and smartphone sensors

A. An animal caregiver and animal breeding rooms.

The body state, squatting (left) and standing (right)

B. Work positions of tasks 1–5 in the breeding room.

C. Smartphone attached to the front waist with three built-in sensors of motion space.

D. A smartphone fixed inside a waterproof case (12.6 cm × 6.6 cm × 8.9 cm) on a belt.

Participants were asked to wear the smartphone and case tightly around the waist.

Fig. 2. Comparison between smartphone and research-grade sensors in human motion sensing

Preliminary justification for human motion sensing by averaging 5-Hz signals of four smartphone sensors A–D over 30 s via comparison with higher precision accelerators in simple optimized motion tasks of 1/30 Hz. Each pair of a trend graph (left) and FFT spectrogram (right) were derived from four 600-s-cycle and 30-s-cycle activity tasks averaged for four participants. (Horizontal and vertical axes: time during tasks and intensity of the sensor signal respectively.)

Fig. 3. Raw signal trend waves (top) and FFT power spectrograms (bottom)

A series of examples acquired by eight signal subtypes of three kinds of mobile sensors during a participant's caring for animals in tasks 1 to 3. (Horizontal and vertical axes: time during tasks and intensity of the sensor signal respectively.)

Fig. 4. Eigenvector clustering between psychology and environment with behavioural characterization obtained employing the LMM and PCA

Grey arrows are of eigenvectors extended from the average centre. The plotted position of each number symbolising the behavioural factor according to Table 2 indicates the coordinate of the PCA score. The diagrams explain the characterized behaviours prominently plotted by PCA scores. The graph centre is the average of the plots.

(PC axes: principal component)

Fig. 5. Three parallel shifts of environmental scores

- A. Ambient relative humidity
- B. Ambient temperature
- C. Outdoor temperature

Figure(1)

Figure(2)

Figure(3)

Figure(4)

Figure(5)