Estimation of Affective State based on Keystroke and Typing Vibration during Computer-Mediated Communication

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Abstract: In recent years, the use of computer-mediated communication (CMC), that is, communication among people through computers, has increased. Knowing the message sender's affective state is essential for understanding the contents of the message correctly. However, it is difficult to interpret this state because of the non-availability of nonverbal information from the sender during CMC. Although attempts have been performed to estimate affective state, there is a challenge of high measurement load. In this paper, we propose an estimation of valence and arousal using keyboard input and typing vibration information as a method to estimate the sender's affective state with a low measurement load during CMC. We conducted experiments to obtain keyboard input and typing vibration information for estimating valence and arousal. This estimation was performed by extracting features from the information using a support vector machine, and cross-validation was conducted to verify our method. Therefore, the valence and arousal were estimated at accuracies of 69.8% and 71.1%, respectively, for unlearned participants' data.

1 INTRODUCTION

With the widespread use of the internet, computer-mediated communication (CMC) has become one of the most popular modes of communication. Several companies have introduced business chat tools along with the popularization of CMC. Knowing another person's affective state plays a significant role in interpreting the message being conveyed correctly (Kruger et al., 2005). Therefore, for effective CMC, it is essential to understand the valence and arousal levels of the communicators. However, unlike in the case of face-to-face conversation, nonverbal information, such as tone, facial expression, and gestures, which aid in understanding the affective state, is unavailable during CMC.

Study on the estimation of the affective state using biometric information has been published in recent years. Valence and arousal have been estimated by constantly measuring the galvanic skin response (GSR) or heart rate (HR) while using CMC (Wang et al., 2004; Wu et al., 2010). However, the challenge with measuring biometric information is that electrode pads need to be attached directly to the body, which is not very practical. In recent studies, it has been reported that variations in keyboard operation depend on the affective state. Therefore, in this study, we decided to obtain information on keyboard operation to estimate valence and arousal during CMC, which implies a low measurement load. In addition, because computer keyboards are routinely used in the workplace, obtaining information from the keyboard is advantageous in that this process does not interfere with the operator's current task.

Whereas a high correlation has been suggested between valence and keyboard input information, a low correlation has been reported between arousal and keyboard input information (Salmeron-Majadas et al., 2014). Some studies have tried to improve the accuracy of arousal estimation using information on the typing force used (Lv et al., 2008). To this end, they utilized a keyboard having an embedded pressure sensor to measure typing pressure with respect to typing force information. However, this method requires a unique keyboard, which is limited in terms of availability.

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Considering all these factors, we focused on vibration as a feature of typing. The keyboard vibrates slightly owing to typing, and this vibration varies depending on the typing force. We considered the fact that the typing force affects the amplitude of the vibration wave.

On the basis of the preceding discussion, we propose a method to estimate valence and arousal using keyboard input and typing vibration information. To measure the typing vibration information, we employed a device that can measure acceleration simply through connection via a USB port on a computer. In this study, we estimated valence and arousal using the data obtained through this device. The contributions of our study are as follows:

- We propose a method for the estimation of valence and arousal using keyboard input and typing vibration information.
- We demonstrate that valence and arousal can be estimated with an accuracy of 69.8% and 71.1%, respectively.
- We determine the essential features required for the estimation of valence and arousal.

2 RELATED WORKS

So far, studies investigating the affective state during CMC have broadly utilized either biometric or keyboard input information.

2.1 Biometric Information Measurement

Wang et al. measured the GSR continually during CMC to estimate the valence and arousal (Wang et al., 2004). Electrodes were attached to the participants' middle and index fingers for the GSR measurement. Hassib et al. and Wu et al. measured the HR, which reflects sympathetic nerve activity, constantly and estimated the affective state (Wu et al., 2010; Hassib et al., 2017). In that study, a chest-strap-type electrocardiographic monitor was attached to the participants' bodies to measure the HR. Lin et al. classified four emotions (joy, anger, sadness, and pleasure) determined using participants' electroencephalographs (ECCs) (Lin et al., 2010). Bos attempted to estimate valence and arousal from ECCs (Bos et al., 2006). In their study, a device, in which embedded electrodes were used to cover the head, were used to monitor the ECCs. However, we considered the fact that these studies encountered the challenge of high measurement load because of the need for the sensor to be worn all the time.

2.2 Keyboard Information Measurement

As a method using low measurement load, estimation of the affective state using keyboard information has been explored in many studies.

Serigo et al. tried to estimate valence and arousal using keystroke information, digraphs, trigraphs, and computer mouse motion information (Salmeron-Majadas et al., 2014). Both keystroke and computer mouse motion information had a high correlation with valence and a slightly low correlation with arousal. Khan et al. estimated participants' valence and arousal using the average time interval between typing events, number of times windows were switched, number of typing events, and computer mouse motion information (Khan et al., 2013). Bixler et al. determined the total time taken to type a sentence, number of typing events, typing redundancy (calculated by tracking the Backspace key events), and the time interval between typing events (Bixler and D'Mello, 2013) to recognize the participants' consciousness (bored, focused, or neutral). Khanna et al. and Felipe et al. estimated the participants' affective states using the following features: four statistics (mode, standard deviation, variance, and range) of typing speed and number of typing events, time interval between typing events, and number of Backspace key events (Khanna and Sasikumar, 2010; Felipe et al., 2012).

A keyboard that could measure typing pressure (hereinafter, referred to as the pressure-sensitive keyboard) to estimate the affective state was also proposed. Hernandez et al. monitored typing pressure and computer mouse events using a pressure-sensitive keyboard and capacitive computer mouse (Hernandez et al., 2014). The work suggested that the typing pressure and computer mouse click pressure can be used to determine whether an operator is typing under high or low stress. Hai et al. estimated six emotions (neutral, anger, fear, happiness, sadness, and surprise) based on typing pressure distribution captured using a pressure-sensitive keyboard (Lv et al., 2008). However, the keyboard is a unique keyboard that aids pressure measurement, and there are restrictions regarding the environment in which it can be used.

Therefore, a method that entails low measurement load is required to estimate valence and arousal such that the current task at hand is not disturbed.

3 ACCELERATION-MEASUREMENT DEVICE

As mentioned earlier, we utilized typing vibration information as one of the inputs for estimating valence and arousal. To this end, we designed a device containing an acceleration sensor (hereinafter, referred to as the acceleration-measurement device) to easily measure the typing vibration information (Figure 1). The vibration generated by typing propagates to the computer, which can be measured by connecting the acceleration-measurement device to the USB port on the computer. This device consists of an Arduino Micro (Arduino A000053) and an acceleration sensor (Kionix Inc. KXR94-2050) and connector (Figure 1), and the acceleration values generated by the typing vibration as well as timestamps are obtained from the device at a sampling rate of 1800 Hz. The data are sent from the device to the computer through serial communication at a communication baud rate of 9600 bps.

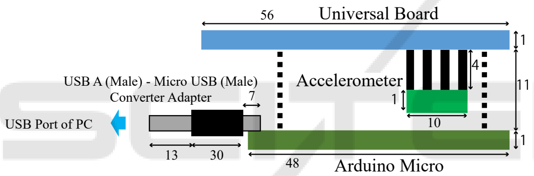

Figure 1: Acceleration-measurement device.

4 FEATURE EXTRACTION

We propose to extract the relevant features from keyboard input and typing vibration information and construct a classifier using a support vector machine (SVM), which employs features as input and outputs valence and arousal. Table 1 lists the features considered in this study. The message composition efficiency and keystroke features were extracted as the features of keyboard input information. In this study, keystroke features include the time interval between typing events and the typing frequency. The amplitude and frequency of vibration were extracted from the vibration information.

4.1 Keyboard Input Information

Messages are edited before being sent to another person. We considered this process of editing to represent the affective state. Therefore, we focused on the ratio of the number of words in a message to the number of typing press events required for composing the

Table 1: Features considered in this study.

type	feature		note	quantity
keyboard input information	message composition efficiency		$\frac{number\ of\ words}{number\ of\ press\ events}$	1
	keystroke	time interval between typing events	press to press	10
			press to release	10
			release to press	10
			release to release	10
		typing frequency	Backspace	1
			Enter	1
			Space	1
typing vibration information	typing amplitude		character (A to Z)	10
			Backspace	10
			Enter	10
			Space	10
	vibration frequency		first	10
			second	10

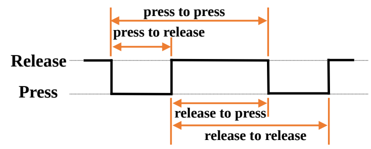

Figure 2: Time interval between typing events.

message (hereinafter, referred to as message composition efficiency) as the feature of message editing.

When CMC is used, a typing event, i.e., "press" or "release" of a key, occurs. The time interval between typing events is used to describe typing speed. While the feature of the time interval between typing events was extracted, two timestamps were obtained during typing, and four features (the time taken from press to press, press to release, release to press, and release to release) were calculated (Figure 2). The typing frequency was calculated using the ratio of the number of press events between a specific key and all the keys in a message.

Thus, the following indexes were used as features of keyboard input information.

- Ten statistics associated with each of the time intervals between typing events (press to press, press to release, release to press, release to release)
- Typing frequency (Backspace, Enter, Space)
- Message composition efficiency

The ten statistics were the mode, median, mean, first quartile, third quartile, standard deviation, variance, median absolute deviation (MAD), skewness, and kurtosis.

4.2 Typing Vibration Information

The typing vibration information was obtained using the acceleration-measurement device (Figure 1). This subsection details the features extracted from the typing vibration information.

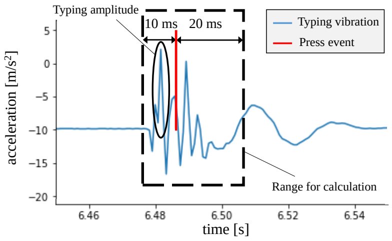

Figure 3: Calculation of typing amplitude.

To obtain information regarding the typing force, the amplitude of the typing vibration was determined. When the amplitude of a specific key being typed is extracted from the typing vibration information, it is necessary not to extract the amplitude of the typing before and after the specific key being typed. Further, the maximum amplitude timestamp is often later than the typing timestamp because the oscillator errors of Arduino Micro cause a shift in the acceleration timestamp. For these reasons, the typing amplitude was defined as the maximum value in the range from 10 ms before to 20 ms after the typing instant.

We considered utilizing the formant frequency as the feature associated with the frequency of typing vibration and used the first and second formant frequencies (hereinafter, referred to as the first vibration and second vibration frequencies, respectively). Each feature was extracted as follows:

1. Extract acceleration values in the range from 500 ms before to 500 ms after the typing instant.
2. Calculate spectrum envelope using linear prediction (LPC).
3. Define the lowest frequencies of the upward peaks as the first and second vibration frequencies, respectively.

Figure 4 depicts the first and second vibration frequencies and the spectrum envelope obtained from the actual typing. The Enter key is often used at the end of a sentence during typing; therefore, the sharpness of typing the Enter key is an indicator of the message sender's affective state. Therefore, the first and second vibration frequencies in typing just the Enter key were used.

The features related to typing vibration information are as follows:

- Ten statistics associated with the typing amplitude (characters, Backspace, Enter, Space)
- Ten statistics associated with the first and second vibration frequencies in the typing amplitude

The ten statistics were the same as those listed for the keyboard input information.

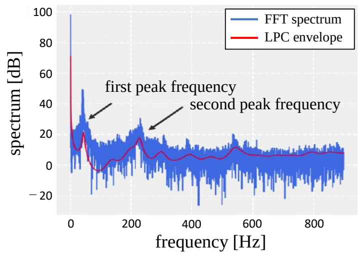

Figure 4: Spectrum envelope and vibration frequencies.

4.3 Classifier

If the level—high or low—of the valence and arousal can be known during CMC, it can be used as a substitute for nonverbal information. Therefore, it is desirable that the classifier used to estimate valence and arousal specializes in binary classification problem. In this study, the SVM, which satisfies the specialization, was applied as a classifier. The radial basis function (RBF) was applied as the Kernel function, and hyperparameters of SVM were determined exploratory by grid search.

5 EXPERIMENT

To employ the SVM as a classifier that estimates valence and arousal using keyboard input and typing vibration information, we recruited participants and conducted experiments to collect the data that were used for learning. In the experiments, the participants were asked to discuss with experimenter. During the discussion, keyboard input and typing vibration information were gathered, which were used as inputs for the SVM. Its outputs were the valence and arousal. We verified the generalized performance of the classifier through cross-validation. The Ethics Committee of the University of Tokyo approved the experiment (No. 19-360). Written informed consent was obtained from every participant.

5.1 Experiment Design

The participants in the experiment were eight healthy adult males (aged 23.6 $\pm$ 0.32 yr). They were asked to prepare certain reports and discuss them through CMC using Slack (Slack, 2019), a business chat tool. During the communication, the keyboard input information was obtained, and the typing vibration information was collected using the acceleration-measurement device. The experimental procedure is illustrated in Figure 5. Two different conditions (positive and negative), which will be described later, were

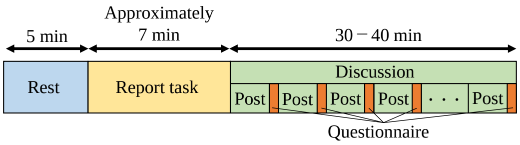

Figure 5: Experimental procedure.

implemented three times for each participant, so that each participant conducted the experiment six times.

5.1.1 Stage I: Rest

The participants rested for 5 min. The aim of this stage was to calm their affective states.

5.1.2 Stage II: Report Writing

The participants alone thought of solutions to a social problem and prepared related reports for about 7 min. After completion, they posted their reports onto the chat space.

5.1.3 Stage III: Discussion

The reviewer and participants discussed the posted reports through the chat space. To impact the participants' affective states, two conditions, positive and negative, were prepared and implemented through the reviewer's behavior. Under the positive condition, the reviewer's response was designed to affirm the proposals of the participants to create a good impression in the participants' minds. Under the negative condition, the reviewer posted comments that rejected the participants' proposals. During the discussion, the keyboard input and typing vibration information was measured using the laptop used by the participants. To obtain references of the participants' valence and arousal for each message, the participants were asked to evaluate their affective states through a questionnaire (Figure 6).
The discussion was continued for about 30–40 min with 10 messages from each participant being sent.

Figure 6 exhibits the questionnaire based on Russell's valence–arousal model (Russell, 1980). The horizontal and vertical axes represent valence and arousal, respectively. The questionnaire consists of 7 $\times$ 7 = 49 block check boxes including the axes, which correspond to valence = 0 and arousal = 0. The participants indicated their own affective states by checking the appropriate boxes.

5.2 Analysis

Using the SVM to estimate the valence and arousal, we conducted a two-category classification.

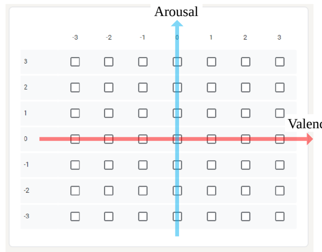

Figure 6: **Questionnaire used in experiment.** Horizontal and vertical axes represent levels of valence and arousal, respectively. With respect to the corresponding axes, higher than 0 and lower than 0 indicate high and low valence and arousal, respectively.

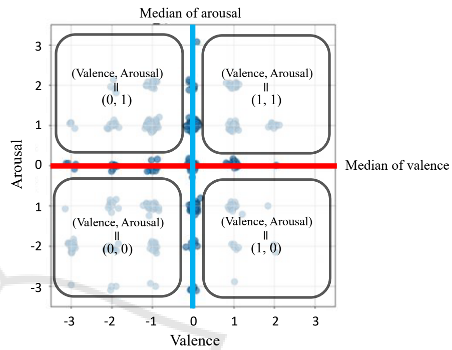

Figure 7: **Distribution of questionnaire results and labeling process.** The diameter of the gray circle represents the number of responses.

5.2.1 Data Preprocessing

The references of valence and arousal were labeled as high or low for conducting the two-category classification. First, the medians for valence and arousal were calculated in all the participants' references. Next, the questionnaire results higher (lower) than the respective medians were labeled high (= 1) (low (= 0)). The questionnaire results that matched the median were removed for classification. After all, the median was 0 for both valence and arousal. The distribution of results and labeling process are depicted in Figure 7.

5.2.2 Classification I: Two-category Classification for Randomized Data Set

Using SVM, we classified the valence and arousal labels into two categories. To evaluate the classifier, four-fold cross-validation was conducted using randomized data including those from all eight participants. The accuracies of valence and arousal in the 28 cross-validations are presented as box-and-whisker plots in Figure 8. The average accuracies and standard deviations were 81.2% $\pm$ 4.7% for valence classification and 78.2% $\pm$ 2.4% for arousal classification.

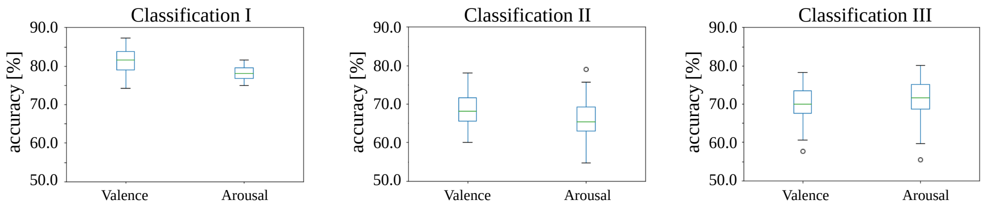

Figure 8: **Accuracy of cross-validation in each classification.** In Classification I, four-fold cross-validation was conducted using randomized data set. In Classification II, cross-validation was conducted using unlearned participants' data for verifying generalization performance. In Classification III, cross-validation was conducted using effective features as input for improving versatility.

5.2.3 Classification II: Two-category Classification to Verify Generality

Considering the fact that individual differences were possible in the features extracted from the keyboard input and typing vibration information, we concluded that the versatility of the classifier would be reduced if the learning and verification data included the same participant's data. To verify the generality of the classifier for unlearned individual data, the eight sets of data obtained were divided into sets of six (for learning data) and two (for validation data). A total of 28 cross-validations, which are the number of cases of division, were conducted to verify the generalized performance of the classifier.

The average accuracies and standard deviations were calculated as 68.5% $\pm$ 4.5% and 66.4% $\pm$ 5.4% for valence and arousal, respectively. The accuracies of valence and arousal in the 28 cross-validations are presented as box-and-whisker plots in Figure 8, which indicates the accuracy varied widely, and it was observed that the generalization was low. The reason for this result is the use of several features with large individual differences. To construct a classifier with generalized performance, it is necessary to use only those features that do not vary depending on the individual in the estimation.

5.2.4 Classification III: Classification using Effective Features

To improve the generality of the classifier with SVM, we considered specifying the features that would be effective for classifying the valence and arousal as high or low. Similar to the case of Classification II, all the data were divided sets of six and two, and a total of 28 cross-validations, which is the number of cases of division, were conducted. We thus concluded that the features frequently confirmed to be significant by the 28 cross-validations were effective for classification. To confirm the effectiveness of the features for a classification model other than SVM, a one-way analysis of variance (one-way ANOVA) test, which is a feature-selection method, depending on each feature, was applied. To investigate whether the high- and low-labeled groups were significantly different for each feature, the test was conducted for each iteration by calculating the p-values for each feature.

Next, we calculated the number of times the significance level ($p<0.05$) was met for each feature. These results indicated that the accuracies for valence and arousal were the highest when the features that met the significant levels more than 24 and 28 times, respectively, were used, as presented in Figure 9, which depicts the accuracy for valence and arousal. The features for valence and arousal used in this classification are presented, respectively, in Table 2 and Table 3. The tables also provide the effective feature changes observed when valence and arousal were high compared to when they were low. For the classification of high or low valence and arousal using the selected features as input, 28 cross-validations were conducted, as in Classification II. The accuracies of valence and arousal in the 28 cross-validations are presented as box-and-whisker plots in Figure 8. The average accuracies and standard deviations were 69.8% $\pm$ 4.8% for valence and 71.1% $\pm$ 5.8% for arousal. When compared with the performance of Classification II, which was carried out using all the features, the generalization performance of Classification III was better.

Variations in more effective feature that met significance level 28 times and that varied specially between high and low, in valence and arousal respectively, are as presented in Figure 10.

6 DISCUSSION

The valence and arousal of participants uncontained in learning data can be estimated at accuracies of 69.8% and 71.1%, respectively, by introducing typing vibration information and using effective features. Table 3 indicates the features that are effective for the estimation of arousal, and 12 of 9 features were related to typing amplitude. Introducing typing vibration in-

Table 2: **Features that frequently met significance level for valence.** The column "change" provides the change of feature observed when valence was high compared to when it was low.

feature			number of times	change
time interval between typing events	press to press	standard deviation	28	decrease
time interval between typing events	press to release	mean	28	decrease
time interval between typing events	press to release	variance	27	decrease
time interval between typing events	press to release	MAD	27	decrease
typing amplitude	Backspace	MAD	26	decrease
time interval between typing events	release to press	standard deviation	25	decrease
time interval between typing events	press to release	third quartile	24	decrease
typing amplitude	Backspace	standard deviation	24	decrease
time interval between typing events	release to release	standard deviation	24	decrease
time interval between typing events	press to press	standard deviation	24	increase

Table 3: **Features that frequently met significance level for arousal.** The column "change" provides the change of feature observed when arousal was high compared to when it was low.

feature			number of times	change
typing amplitude	characters	standard deviation	28	increase
typing amplitude	characters	mean	28	increase
typing amplitude	Space	mean	28	increase
typing amplitude	characters	MAD	28	increase
typing amplitude	characters	median	28	increase
typing amplitude	characters	first quartile	28	increase
typing amplitude	characters	third quartile	28	increase
typing amplitude	Space	MAD	28	increase
time interval between typing events	press to release	mean	28	decrease
time interval between typing events	press to release	third quartile	28	decrease
time interval between typing events	press to release	first quartile	28	decrease
typing amplitude	Space	variance	28	increase

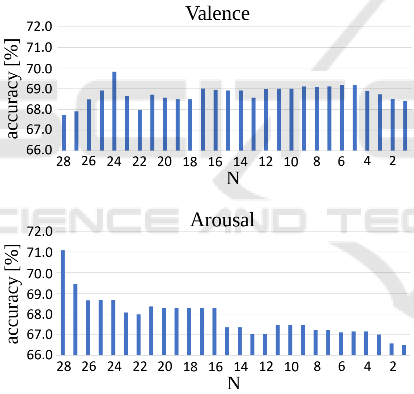

Figure 9: **Accuracy for valence and arousal in Classification III.** Estimation accuracy for valence (top) and arousal (bottom) when using features that met significant level ($p<0.05$) more than N times during cross-validation.

formation generalized the classifier's performance for the estimation of arousal. However, due to the small size of participants (= 8 males), the above should be interpreted as a view based on preliminary experimental results. Khan et al. and Serigo et al. utilized information regarding computer mouse events and window switching in addition to keyboard input information for estimating the affective states (Khan et al., 2013; Salmeron-Majadas et al., 2014). In this study, we considered that the estimation of valence and arousal at an accuracy of approximately 70% without these information during CMC, computer mouse operation and window switching are rarely used, was a huge contribution.

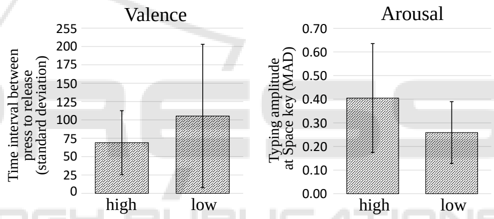

Figure 10: **Variation in effective features in valence and arousal.** Standard deviation of the time interval between press to release in valence (left), and MAD of the typing amplitude at Space key in arousal (right).

The following trends are noticed in Classification III. Compared with when valence is low, especially, the time interval between typing events is shorter and its dispersion is also lower when the valence is high. This implies that the typing speed is faster and constant when the valence is high. Compared with when arousal is low, the typing force is stronger and its dispersion is higher when the arousal is high. This implies that the typing force is stronger and constant when arousal is high. When valence was high, the participants actively discussed the reports with the reviewer, their replies also came up smoothly, which made the typing speed faster and led to monotonic typing. Because of excitement, regardless of whether their affective state was positive or negative, the participants typed strongly on the keyboard when arousal was high.

In the experiment described in this paper, the effect of variation in features on valence tended to be contrary to what has been reported in related works. In Serigo et al.'s study, the time interval between typing events was longer when the valence was high compared with when the valence was low (Salmeron-Majadas et al., 2014). Our experiment reported this time as being shorter. This observation can be attributed to the specific experimental design implemented. Serigo et al. introduced a time limit for task completion to create stress on the participants, thus impacting their affective states. In our study, the participants' affective states were impacted through a certain communication stress, such as strict replies from the reviewer, to simulate the understanding that the stress is usually caused by the actual content of the communication. Hence, the results obtained through our experimental design are useful in understanding the impact on affective state during CMC.

The features related to vibration amplitude met a significant level ($p<0.05$) for classifying high or low valence and arousal in several cases. Thus, it was established that the features related to typing force are effective in the estimation of arousal.

7 CONCLUSION

In this paper, we proposed a method to estimate valence and arousal using keyboard input and typing vibration information. Effective features were selected through statistical tests, and the unlearned participants' data were classified to investigate versatility. This time, the average accuracies and standard deviations were $69.8\% \pm 4.8\%$ for valence and $71.1\% \pm 5.8\%$ for arousal. Thus, it was established that it is possible to estimate valence and arousal with high accuracy for the unlearned participants' data by specifying the features and using keyboard input and typing vibration information.

In future study, it is necessary to further improve the accuracy by selecting features specifically suitable for each individual. Further, the determination of essential features that are common across keyboards is required since each keyboards have different characteristics.

It is expected that the findings of this study will facilitate smooth computer-mediated communication in the near future, avoiding misinterpretation of other people's messages.

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