Analysis of Teens' Chronic Stress on Micro-blog

Yuanyuan Xue[1,2](✉), Qi Li[1], Liang Zhao[1], Jia Jia[1], Ling Feng[1], Feng Yu[3], and David A. Clifton[4]

[1] Department of Computer Science and Technology, Tsinghua University, Beijing, China
{xue-yy12,liqi13,jing-zhao11}@mails.tsinghua.edu.cn, {jiajia,fengling}@mail.tsinghua.edu.cn

[2] Department of Computer Technology and Application, Qinghai University, Xining, China

[3] Department of Psychology, Tsinghua University, Beijing, China
yufeng10@sem.tsinghua.edu.cn

[4] Institute of Biomedical Engineering, University of Oxford, Oxford, UK
davidc@robots.ox.ac.uk

Abstract. Statistics show that more and more teenagers today are under the stress in all areas of their lives from school to friend, work, and family, and they are not always able to use healthy methods to cope with. Long-term stress without proper guidance will lead to a series of potential problems including physical and mental disorders, and even suicide due to teens' shortage of psychological endurance and controllability. Therefore, it is necessary and important to sense teens' long-term stress and help them release the stress properly before the stress starts to cause illness. In this paper, we present a micro-blog based method to recognize teens' chronic stress by aggregating stress detected from micro-blog. In particular, we analyze the characteristics of teens' chronic stress, and identify five types of chronic stress level change patterns. We evaluate the framework through a user study at a high school where the 48 participants are aged 16–17. The result provides the evidence that sensing teens' chronic stress is feasible through the open micro-blog, and the identified stress level change patterns allow us to find useful regulations of teens' stress transition and to give sensible interpretations.

Keywords: Teens · Chronic pressure · Stress transition · Micro-blog

1 Introduction

1.1 Motivation

No one lives a stress-free life. Anything that poses a challenge or a threat to our well-being is a stress. The American Heritage Medical Dictionary defines *stress* as a physical or psychological stimulus that can produce mental or physiological reactions which may lead to illness [1]. Stress can be divided into *acute stress* or *chronic stress*. Acute stress is usually short-lived and can be beneficial, as it can

W. Cellary et al. (Eds.): WISE 2016, Part II, LNCS 10042, pp. 121–136, 2016.
DOI: 10.1007/978-3-319-48743-4_10

enhance alertness and improve productivity [2]. In contrast, chronic stress is long-lived. It is the response to emotional pressure suffered for a prolonged period over which an individual perceives s/he has no control. While the immediate effects of stress hormones are beneficial in a particular situation, long-term exposure to stress creates a high level of these hormones that remains constant. This may lead to high blood pressure and subsequently heart disease, damage to muscle tissue, inhibition of growth, suppression of the immune system, and damage to mental health [3]. In view of the severe consequence of chronic stress, it is quite important to catch it in time.

With the rapid economic development, chronic stress has become an epidemic in our modern society, and people almost accept it as a way of life. Particularly for teenagers, they have to face heightened stress due to the many changes experienced concomitantly. When teens are overloaded with long-term chronic stress, inadequately managed stress can lead to anxiety, withdrawal, aggression, physical illness, or poor coping skills such as drug/alcohol use. It could also trigger or worsen depression [4], social isolation, and aggressive miss-behaviors [5]. To the extreme, injury to either teenagers themselves or others will happen. The campus gunman, Elliot Rodger, posted a video of himself on YouTube, saying he had been suffering long-lasting stress of loneliness before the campus killing in Santa Barbara in USA [6].

Hence, being aware of the existence of chronic stress and helping stressful teenagers control and manage chronic stress before it becomes severe enough to cause illness are particularly important.

1.2 Existing Solutions

Traditional stress analysis and detection techniques use subjective questionnaires or various objective sensors to monitor the changes and predict the trends of *physiological signals* and/or *physical signals* for people under stress [7–9]. *Smart phones* as a kind of speech sensor were also exploited in [10,11], focusing on cognitive stress and stressor frequency estimation rather than the type and severity of stress. The limitations of these methods are the invasion or inconvenience caused by the body contact and the deviation induced by physical excise. Recently, micro-blog offers another low-cost sensing channel to obtain people's self-expressed contents and behaviors, from which some emotional signals could be captured and analyzed. [12–16] evaluated whether people are in the risk of depression by analyzing their twitting behaviors. Oriented at the youth group, [17–19] investigated a number of teens' typical tweeting behaviors that may reveal adolescent stress, and built a micro-blog based platform to sense and help ease teenagers' mental stress. But, aforementioned analysis stopped at detecting adolescent stress category and stress level from teenagers' tweets. None investigates further to design an approach to differentiate whether a teen suffers chronic stress upon the aggregation of stress of tweets within time periods on micro-blog.

1.3 Our Work

The aim of this study is to analyze and distinguish teenagers' acute and chronic stress through the social media micro-blog. Chronic stress could appear continuously or discontinuously and its level may vary over time during the stress period. Understanding teens' chronic stress level change patterns and features could help us track and predict teens' stress trend, then further provide proper intervention to avoid possible severe consequences.

Here, we turn to micro-blog for teens' chronic stress detection for the following reasons. Firstly, micro-blog keeps track of teens' long-term tweeting contents and behaviors, and it is possible to detect and associate stress within different time scopes, which is difficult for wearing body-contact sensors and taking the measurements. Secondly, teenagers tend to record details of their daily life and feelings on micro-blog, making the acquisition of teens' emotional states possible. Furthermore, based on the sensing results, effective and prompt intervention and interaction with teens under stress can be easily implemented through the lively micro-blog channel.

The contributions of this paper can be summarized as follows.

- By aggregating teens' stress levels from individual tweets, we design a method to differentiate teen's chronic stress over a time period.
- We analyze the characteristics of teens' chronic stress, and identify five types of chronic stress change patterns.
- We conduct a user study testing the accuracy of the proposed method with teenagers recruited from a local school, and experimentally analyze the reasons for different chronic stress level change patterns.

To our knowledge, this is the first attempt in the literature to analyze and identify teenagers' chronic stress, as well as different chronic stress level change patterns, on micro-blog social media.

2 Related Work

2.1 Stress Detection by Subjective Questionnaires and Psychologists

The first method uses subjective questionnaires or individual/group meetings with psychologists to analyze users' stress situations. This method needs high cooperation of users and relies on people's ability to recall their experiences.

2.2 Stress Detection from Physiological Signals

Because stress will induce the variation of physiological and physical signals of the body, there is a rich body of work using objective physiological and physical signals to detect stress. Typical physiological measures include galvanic skin response (GSR), heat rate variability (HRV), electroencephalogram

(EEG), electrocardiogram (ECG), blood pressure, electromyogram, and respiration. [20] found skin conductivity and heart rate metrics have close correlations with driver's stress level, and used electrocardiogram, electromyogram, skin conductance, and respiration for driver's stress detection [21]. [22] applied the non-linear system identification technique to HRV for continuous mental stress monitoring. The above experimental results came from the laboratories where subjects were under a stationary state. For people on the move, [23] combined ECG, GSR, and accelerometer gathered from 20 participants across three activities (sitting, standing, and walking) to differentiate physiological signals generated between physical activity and mental stress. [24] investigated the differences of EEG characteristics (overall complexity and spectrum power of EEG bands) collected from two groups of people - high stress versus moderate stress. The results showed that those with chronic stress have higher left prefrontal power.

2.3 Stress Detection from Physical Signals

Although physiological measures can achieve good accuracy in mental stress detection, it may make people discomfort, slightly conflicting air, or even more stressful increase due to its invasiveness. Some physical measures (e.g., voice, gesture and interaction, facial expressions, eye gaze, pupil dilation and blink rates) are thus taken for stress detection as non-invasive measures, since they do not need to put the contact sensors on human bodies. Voice-based stress detection has received much attention in recent years due to its observable variability when response to stressors. [25] presented a stress detection method by computing prosodic, voice quality, and spectral features on variable window sizes. Smart phones were also used as a kind of sensor to detect people's mental stress by analyzing their voice variation in diverse conversational situations [10,11]. Besides voice, [26] analyzed people's mouse movements and found that people click mouse button harder as their stress decrease. [27] proposed a stress recognition method based on pupil videos obtained from video camera. Considering the contact sensors need specialists to install and monitor, which causes inconvenience to people's daily life, [28] used a low-cost webcam that recovered the instantaneous heart rate signal from video frames of human faces for mental stress detection. [29] further used features extracted from GSR and/or speech signals to train four types of classifiers, and the result showed that SVM classifiers can reach better accuracy than other classifiers for stress detection.

2.4 Stress and Depression Detection from Micro-blog

The popularity of micro-blog offers another medium for sensing people's mood. [13,14] built a statistical classifier to estimate whether people are in the risk of depression by analyzing their twitting behaviors before being diagnosed. The experimental results demonstrated that social media contained useful cues in predicting individual's depression tendency. Recently, [17] investigated a number of teens' typical tweeting behaviors that may reveal adolescent stress, and applied five classifiers to teens' stress detection. [18] trained a deep sparse neural network to detect psychological stress from cross-media micro-blog. So far, teen's stress detection is conducted on the basis of individual tweets. Aggregation of stress levels revealed from tweets over a time period to identify teen's chronic stress and different chronic stress change patterns, have not been investigated yet. In this paper, a user study recruits 48 teenagers from a local high school and estimates the accuracy of the proposed method. Besides, some interesting findings are also found through the user study.

3 Problem Statement

Considering the characteristics of teenagers' micro-blog behaviors, [17,18] developed techniques to sense teenagers' stress level from each individual tweet of the four major categories: study, self-cognition, inter-personal, and affection. Six ranks: *none, very light, light, moderate, strong, very strong* are adopted to measure stress levels, where *none* indicates no stress. For computation purpose, we use integer set $\mathcal{S} = \{0, 1, 2, 3, 4, 5\}$ to represent the above labels. Let (t, w) be a tweet w posted at time t. Function $Stress(t, w) = s$ returns a detected stress level $s \in \mathcal{S}$ from tweet w.

To further sense chronic stress, we investigate a sequence of teen's tweets during a time period and aggregate the detected stress level of each single tweets.

Definition 1. *Let $I = [I.s, I.e]$ be a time period I starting time $I.s$ and ending time $I.e$. The temporal length of I is $|I| = I.e - I.s$, which can be a day, a week, a month, etc. Let $W(I) = \langle (t_1, w_1), (t_2, w_2) \cdots, (t_m, w_m) \rangle$ (for $I.s \leq t_1 \leq \cdots \leq t_m \leq I.e$) denote a **tweet sequence within time period I**, where tweets $w_1, w_2, \cdots, w_m$ were posted by a teenager chronologically on micro-blog at time $t_1, \cdots, t_m$, respectively.*

Definition 2. *Applying the stress detection function $Stress(t,\ w)$ upon each tweet in $W(I)$, we can obtain a corresponding **stress level sequence in time period I**, denoted as $S(W(I)) = \langle Stress(t_1, w_1), Stress(t_2, w_2), \cdots, Stress(t_m, w_m)\rangle = \langle s_1, s_2, \cdots, s_m\rangle$, where for $\forall i$ $(1 \leq i \leq m)$ $(s_i \in \mathcal{S})$. I is called a **stress existing time period**, if and only if $\exists i (1 \leq i \leq m)$ $(s_i > 0)$.*

As chronic stress is only meaningful for a relatively long time interval, and should exist frequently across the whole period, we give the following definition for chronic stress.

Definition 3. *Let $\mathcal{I} = [I_1, I_2, \cdots, I_n]$ be a time interval, which is divided into n successive time periods of equal temporal length, where for $\forall i$ ($1 \leq i \leq n-1$) ($I_i.e = I_{i+1}.s$) $\wedge$ ($|I_1| = |I_2| = \cdots = |I_n|$). For a list of tweet sequences posted within $\mathcal{I}$, $\mathcal{W} = [W(I_1), W(I_2), \cdots, W(I_n)]$, and a list of stress level sequences within $\mathcal{I}$, $\mathcal{S}(\mathcal{W}) = [S(W(I_1)), S(W(I_2)), \cdots,\ S(W(I_n))]$, the **stress coverage ratio within $\mathcal{L}$** is computed as the number of stress-existing time periods in $\mathcal{I}$ versus the total time periods number n.*

Assume $\mathcal{I}$ is a stress existing time period. $\mathcal{I}$ is called a ***chronic stress existing time period****, if and only if (1) the temporal length of $\mathcal{L}$ is greater than threshold τ_t, and (2) the stress coverage ratio within $\mathcal{L}$ is greater than a threshold τ_c. Based on teenagers' regular schedule, $\tau_t = 1$ month, and $\tau_c = 100\,\%$ for simplification of basic model in this study.*

4 Method

4.1 Gaussian Process for Single Tweet Stress Detection

We extract 9 features from teens' micro-blogs to characterize the postings related to stress. The features can be categorized into two types: content-centric (i.e., linguistic content, number of negative emotion words, shared music/picture genres, number of positive and negative emoticons, number of exclamations and question marks, emotional degree lexicons) and context-centric (abnormal tweeting time and frequency). From each teen's tweeting/retweeting behavior, we extract and analyze these features, and then employ a Gaussian Process classifier to perform single-tweet based stress detection. Several of these features are motivated from [17], where greater details can be accessed by the readers.

Based on the content and context features extracted from teens' tweets, we employ the Gaussian Process (GP) framework to learn the stress level (categorized into 6 levels: "No Stress", "Very Light", "Light", "Moderate", "Strong", "Very Strong") for each tweet, which offers a principled means of performing inference over noisy data. The significant reasons we adopt Gaussian Process are the notion of GP as a distribution over functions and its best performance for stress detection on micro-blog [17], thus it is suitable to analyze teens' tweets. Here, we still use 6 stress levels defined in previous work to measure individual's stress extent in single tweet. Detailed derivations can be found in [17].

4.2 Stress Aggregation on Single Tweets

Considering teens' routines of study and rest vary weekly, we set the granularity of time interval as "week", namely for the successive time interval $\mathcal{I} = [I_1, I_2, \cdots, I_n, I_m]$, the length $|I_i| (1 \leq i \leq m)$ is a week. Thus, for each teen, we first aggregate stress of single tweets weekly, using three typical functions Avg, Max, Sum to calculate the average, minimal, and maximal stress levels in a week. The aggregated stress value indicates the stress state of each week (whether the teen endures stress in this week or not).

Let $W(I) = \langle (t_1, w_1), (t_2, w_2) \cdots, (t_m, w_m) \rangle$ be a tweet sequence in time period I, and let $S(W(I)) = \langle Stress(t_1, s_1), Stress(t_2, s_2), \cdots, Stress(t_m, s_m) \rangle = \langle (t_1, s_1), (t_2, s_2), \cdots, (t_m, s_m) \rangle$ be a list of stress level sequences detected from $W(I)$ (*Definition 1* and *2*). We have $Avg(S(W(I))) = \frac{\sum_{i=1}^{m} s_i}{m}$, $Max(S(W(I))) = arg_{1 \leq i \leq m}\ max(s_i)$, and $Sum(S(W(I))) = arg_{1 \leq i \leq m}\ min(s_i)$.

We label the aggregation stress result (by $Avg/Max/Sum$ functions) in $|I_i| (1 \leq i \leq m)$ as $\mathcal{S}(W(I_i))$. Thus for a stress level sequence $S(\mathcal{W})$ in time interval $\mathcal{I}$, the aggregation result is $\mathcal{S}(\mathcal{W})$. In our later results presentation, we proved that teens' stress (aggregated weekly) has consistent changing trends under three aggregation methods.

4.3 Detecting Chronic Stress Level Change Patterns

Teen's stress state usually changes over time influenced by environment and personality during the chronic stress interval (for example, stress level rises fast or drops slowly). The changing of teens' stress reflects in the variation between low level and high level stress. Thus, in this paper, we define two stress states: *lower stress* and *higher stress*, and focus on their mutual transition.

Within the continuous chronic stress interval $\mathcal{I} = [I_1, I_2, \cdots, I_m]$ (where the length of $|I_i|(1 \leq i \leq m)$ is one week, $S(W(I_i)) > 0$), a teen has two different stress states *lower stress* and *higher stress*, measured by the stress value threshold τ. For the aggregated stress value $\mathcal{S}(W(I_i))$ of each time period $I_i(1 \leq i \leq m)$, if $\mathcal{S}(W(I_i)) \leq \tau$, I_i is in *lower stress* state; or else I_i is in *higher stress* state. The setting of τ is subject to teen's personality and daily behaviors (here we set τ to be 5 based on the fact of 5 working days in a week).

We define *lower stress* interval as $\mathcal{I}_l = [I_p, I_{p+1}, \cdots, I_k]$, and the adjacent *higher stress* interval as $\mathcal{I}_h = [I_{k+1}, I_{k+2}, \cdots, I_q]$ in time interval $\mathcal{I}$ $(1 \leq p \leq k \leq q \leq m)$, satisfying the following two conditions:

Condition 1: For $\forall i$ (p $\leq i \leq k$), $\mathcal{S}(W(I_i)) \leq \tau$;

Condition 2: For $\forall i$ (k+1 $\leq i \leq q$), $\mathcal{S}(W(I_i)) > \tau$.

Teen's chronic stress state changes from $\mathcal{I}_l$ to $\mathcal{I}_h$ when stress starts worsening. Similarly, transition from *lower stress* to *higher stress* happens when time interval $\mathcal{I}_h$ is in front of $\mathcal{I}_l$ in time line.

Within the *higher stress* time interval $\mathcal{I}_h$, we find the maximal stress level $\mathcal{S}_{peak}(I_h) = S(W(I_{peak}))$, where $S(W(I_{peak})) = arg_{p \leq i \leq k}\ Max(S(W(I_i)))$ $(p \leq i \leq k)$. I_{peak} (the time interval with peak stress value), together with I_p (the start time of $\mathcal{I}_l$) and I_q (the end time of $\mathcal{I}_h$), and divide the stress state transaction from *lower stress* to *higher stress* into three phases in the time line:

Phase 1. Early-Starting Phases stress level increases from $lowerstress$ state to $higherstress$ state, from I_p to I_k, in time span $T_1 = k - p$ (indicated in Fig. 1 with $p1$).

Phase 2. Middle-Rising Phases stress level increases from $S(W(I_k))$ to peak value $\mathcal{S}_{peak}(\mathcal{I}_h)$, from I_{k+1} to I_{peak}, in time $T_2 = peak - (k+1)$ (indicated in Fig. 1 with $p2$).

Phase 3. Late-Decreasing Phases stress level decreases from peak value $\mathcal{S}_{peak}(\mathcal{I}_h)$ to *lower stress* state, from I_{peak} to I_q, in time $T_3 = q - peak$ (indicated in Fig. 1 with $p3$).

Note that the transition between *lower stress* and *higher stress* may occur repeatedly and alternately within a continuous chronic stress interval in reality. We measure the stress level changing speed (in *Phase2*) with the slope from I_k

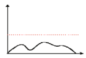
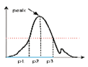
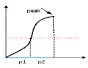
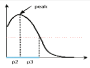
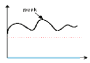
	Pattern ID	Pattern Description	Sub-pattern		
			early (p1)	middle (p2)	late (p3)
	Pattern 1	stable chronic stress	-	-	-
	Pattern 2	stable chronic stress →intensive stress →stable chronic	Fast	Slow	Slow
			Fast	Slow	Fast
			Fast	Fast	Slow
			Fast	Fast	Fast
			Slow	Slow	Slow
			Slow	Slow	Fast
			Slow	Fast	Slow
			Slow	Fast	Fast
	Pattern3	Stable chronic →intensive stress	Fast	Slow	-
			Fast	Fast	-
			Slow	Slow	-
			Slow	Fast	-
	Pattern4	Intensive stress →stable chronic	-	Fast	Fast
			-	Fast	Slow
			-	Slow	Fast
			-	Slow	Slow
	Pattern 5	Last intensive stress	-	-	-

Fig. 1. Five chronic stress level change patterns.

to I_{peak}, denoted as $Speed_{up} = (\mathcal{S}(W(I_{peak})) - \mathcal{S}(W(I_k)))/T_2$. We measure the speed of *Phase1* and *Phase2* by using the time span T_1 and T_2. In our case study, we found 287 stress level transaction cases from 48 teens' tweets, and further calculated the average changing speed of three phases respectively from the 287 transactions, thus obtaining three thresholds for measuring the changing speed of each phase, which are denoted as λ_1, λ_2, λ_3.

Further, we present five stress level change patterns based on the transaction between *lower stress* and *higher stress* states, within the chronic stress interval $\mathcal{I} = [I_1, I_2, \cdots, I_m]$. For each pattern, sub-patterns are defined according to the changing speed (*fast* or *slow*) of three phases, as shown in Fig. 1.

- Pattern 1: within the chronic stress interval $\mathcal{I}$, if for $\forall i$ $(1 \leq i \leq m)$, $\mathcal{S}(W(I_i))$ $\leq \tau$, we call $\mathcal{I}$ a *smooth stress pattern*, indicating that no *higher stress* state appears in this chronic stress interval.
- Pattern 2: within the chronic stress interval $\mathcal{I}$, if there exists three conjoint sub time intervals, $\mathcal{I}_l$, $\mathcal{I}_h$, $\mathcal{I}_l$ in time line, namely stress state changes from *lower stress* to *higher stress* state, then back to *lower stress* state, we call it a *burst stress pattern*.
- Pattern 3: within the chronic stress interval $\mathcal{I}$, if there exists two conjoint sub time intervals, $\mathcal{I}_l$ and $\mathcal{I}_h$ in time line, namely stress state changes from *lower stress* to *higher stress* state and lasts to the end of $\mathcal{I}$, we call it a *gradually intensified and long-lasting pattern*.
- Pattern 4: within the chronic stress interval $\mathcal{I}$, if there exists two conjoint sub time intervals, $\mathcal{I}_h$ and $\mathcal{I}_l$ in time line, indicating that stress changes from

higher stress (at the beginning of $\mathcal{I}$) to *lower stress* state, we call it a *downward stress pattern*.
- Pattern 5: within the chronic stress interval $\mathcal{I}$, if $\forall i$ $(1 \leq i \leq m)$, $\mathcal{S}(W(I_i)) \geq \tau$, we call $\mathcal{I}$ *intensive stress pattern*, showing that the teen keeps in *higher stress* state.

5 User Study

5.1 PSS-14 Questionnaires

Cohen's Perceived Stress Scale (PSS-14) [30] is commonly used to measure human's stress level worldwide in psychology. We take the PSS-14 score value (from 0 to 75, corresponding to none, light, moderate, and strong stress level respectively) as the ground-truth of our general stress detection results.

We invited 48 students (26 girls and 22 boys, aged 16–17) with micro-blog accounts from Xining No. 4 High School to participate in our case study. Getting their consents, we guided the students to fill in the Chinese PSS questionnaire [31] based on their emotional feelings in the last month (from `Nov.26,2014` to `Dec.26,2014`).

Besides, we also add two questions to ask participants to label their characters and micro-blog usage: (1) "*Do you think you are introvert or extrovert?*" and (2) "*Do you prone to express emotions through tweets?*"

5.2 Teens' Tweets from Tencent Micro-blog Platform

We collected 30,041 tweets before 26 December, 2014 of the above 48 students from Tencent Micro-blog Platform, which is similar to Twitter in China. For each teen, the number of tweets ranges from 28 to 3,288, and the time span ranges from 25 weeks to 261 weeks. These tweets provide us with abundant information to detect chronic and acute stress of the participants, and to further analyze their chronic stress level change patterns.

To verify our detection results for chronic stress according to our ground-truth (based on PSS-14 questionnaires), we collected tweets of the 48 teens in the corresponding month (from November 26, 2014 to December 26, 2014). For each teen, the number of tweets ranges from 1 to 94, and the time span ranges from 1 week to 5 weeks.

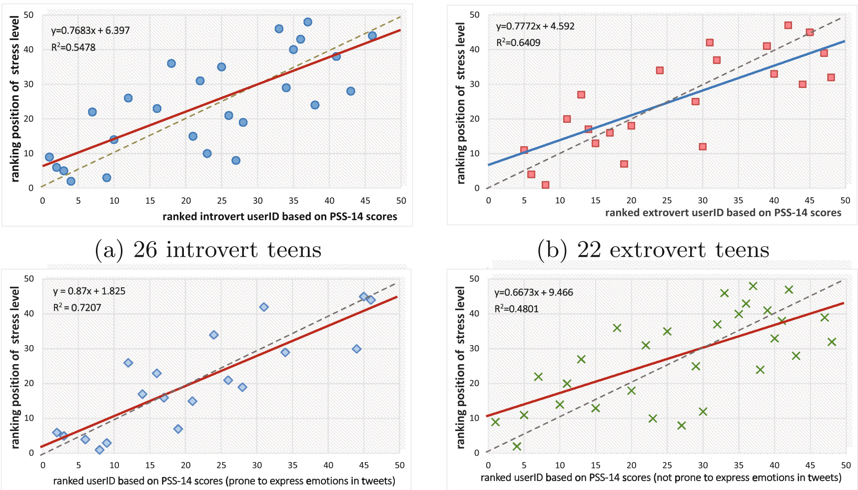
6 Results

To match the four stress levels of PSS-14, we merged our detected "*very light*" and "*light*" stress levels into "*light*" stress level, and "*very strong*" and "*strong*" stress levels into "*strong*" stress level.

6.1 Experiment 1: Teens' General Stress Detection

In this experiment, we used the subset of collected tweets (posted from November 26, 2014 to December 26, 2014), to guarantee the timeliness of our ground-truth (based on PSS-14 questionare). For each student, we detected the stress level of every single tweet, and further computed his/her average stress level in this month. By comparing the stress levels reflected by PSS-14 questionnaire and detected by our approach of each 48 students, the average detection accuracy of our approach is 77.1 %. 25 out of 29 students, who are identified as suffering strong stress by PSS-14, are detected correctly by our approach.

Effect of "Introvert" or "Extrovert" Character on Detection Performance. Figure 2(a) and (b) show the ranking results of PSS-14 and our approach based on the stress levels of 26 introvert students, and 22 extrovert students respectively. We draw the fitting straight line and use R^2 (ranging from 0 to 1) to show the linear correlation degree of data in each sub-figure. The R^2 of 22 extrovert students in Fig. 2(b) shows a higher value of 0.64 than that of 26 introvert students in Fig. 2(a). The difference of R^2 indicates that the ranking result of extrovert teens has a higher linear correlation degree than that of introvert teens.



(a) 26 introvert teens (b) 22 extrovert teens

(c) 19 teens prone to express emotions (d) 29 teens not prone to express emotions

Fig. 2. Ranking results comparison based on stress levels detected by our approach and PSS-14. We rank the PSS-14 scores among 48 teens, and also rank the average stress level of them detected by our approach. We compare the two rank results, using the data fitting method, where the result R^2 ranging from 0 to 1. The greater value of R^2 indicates higher fitting degree of the two ranks.

Students Who Likely Express Emotions on Micro-blog Get Higher Performance. Figure 2(c) and (d) show the ranking results of PSS-14 and our approach based on the stress levels of 19 teens who are prone to expressing emotions in tweets and 29 teens who are not prone to expressing emotions in tweets. The fitting straight line in Fig. 2(c) is nearer to the $y = x$ line and obtains a very high value of $R^2 = 0.72$, which is much higher than $R^2 = 0.48$ in Fig. 2(d), and also higher than the results in Fig. 2(a) and (b).

6.2 Experiment 2: Chronic Stress Detection

In this part, we used whole set of teens' tweets to detect teens' chronic stress and to analyze its change patterns during entire posting time. Given the above definition, in this research, we focused on stress level rather than stress type while detecting chronic stress.

Aggregation Performance. For each teen, we aggregated stress level of single tweets weekly by using three methods: (1) the maximal stress level in a week, (2) the average stress level in a week, (3) the accumulated stress level in a week.

Sensibility of Chronic Stress Intervals. According to the psychological theory, time span of chronic stress could be recognized as "months to years" [32]. Combined with the application scenarios (per semester lasting for 4 months in Chinese high school), the length threshold for chronic stress interval (in Definition 3) is set to 1, 2, 3 and 4 months respectively to explore teens' chronic stress reactions with different baseline time.

Result in Fig. 3 shows that the number of teens suffering from chronic stress gradually decrease as baseline time extended. Combing detection results and teens' tweets, we have observed that nearly half of teens release the stress when semester ends or vacation starts. The rest of teens endure stress coming from families, peers, or bad self-regulation capabilities, which are less affected by outside

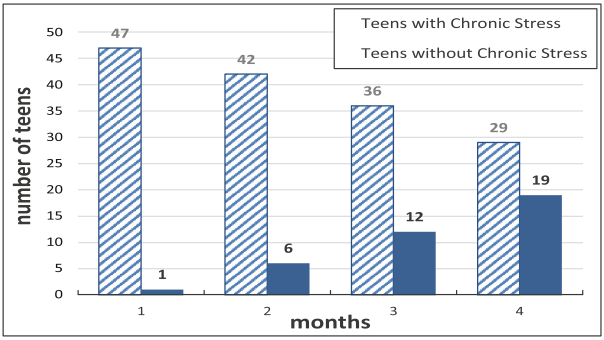


Fig. 3. Number of students with chronic stress, under different settings

world. When time span is set to 1 month, we find that most teens are suffering chronic stress with different periods. So we suggest that coaching or intervention once per month for teenagers be planned, to avoid potential consequences caused by chronic stress.

Performance of Chronic Stress Detection. To evaluate chronic stress detection performance, all participants were asked a question ("In the last year, do you feel nervous and stressed?" 1. Never 2. Seldom 3. Sometimes 4. Often 5. Always), which is regarded as ground-truth for detection result of each teen. To match question answers into the aggregation results (here we choose the average aggregation method, and the other two methods performing the similar trends can also be adopted), we set the rule: answer 1. Never mapping to "None", "2. Seldom" and "3. Sometimes" mapping to "Occasional", and "4. Often" and "5. Always" mapping to "Frequent". Here, we considered the label of "None" as no stress, "Occasional" as temporary stress, and "Frequent" as the chronic stress. Then we chose the minimal size of "1 month" as the threshold of chronic stress interval. The accuracy of detection result is presented in Table 1. Besides, the precision and recall of chronic stress detection can reach to 80.00 % and 66.67 % respectively. Causing relative low recall may be because some participants only posted few tweets during the posting period.

From another perspective, we compared our detection results with the rank of teens' PSS-14 scores (in descending order). Consequently, it reveals that most teens with chronic stress rank high in the list of PSS-14 results. As Table 2 shows, 10 teens with chronic stress are in the top 15, 13 teens are in the top 20, and 15 teens are in the top 25.

Table 1. Confusion matrix of stress detection

PSS-14	Detect		
	None	Occasional	Frequent (chronic)
None	1 (50 %)	1	0
Occasional	1	24 (77.42 %)	6
Frequent (chronic)	0	3	12 (80 %)

Table 2. Top n(15–25) ranks of teens with chronic stress

PSS-14 Rank	Top 15	Top 20	Top 25
Number of teens	10	13	15
Percent	66.67 %	86.66 %	100 %

6.3 Experiment 3: Chronic Stress Change Patterns

According to Definition 5, we explored all the varying patterns existing in the continuous chronic stress intervals of 48 teens. What we concerned more were the duration of low-level stress before its worsening, and the speed of worsening and alleviating. Five patterns were subclassified further in this trial. To describe the properties mentioned above, three parameters were used, including the lasting time of lower stress state $Lastingtime_{low}$, the transition speed from lower state to higher state $Speed_{up}$, and the transition speed from higher state to lower state $Speed_{down}$. We marked $Lastingtime_{low}$ as *slow* when it was greater than average value of lasting time of 48 teens, and marked $Speed_{up}$ and $Speed_{down}$ as *slow* when they were less than average value, the other way round. In such cases, stress level change patterns were classified into 18 sub-patterns (in Definition 4).

Table 3 shows the comparison of occurrence proportion of 5 patterns when the baseline time is set to 1, 2, 3 and 4 months. In general, the overall proportion do not markedly change with baseline time variation. Among these patterns, pattern 1 is the dominant one and then is pattern 2, which means teens usually are under the lower stress while suffering from chronic stress. But when their stress intensifies, it usually turns into a way of increasing first and then decreasing. The small change of percentage of pattern 1 and pattern 2 indicate that the ratio of stress worsening will rise with baseline time increasing.

Table 3. Distribution of 5 chronic stress change patterns in different baseline time

	Pattern 1	Pattern 2	Pattern 3	Pattern 4	Pattern 5
1 month	75.04 %	15.91 %	3.47 %	4.86 %	0.69 %
2 month	74.32 %	17.96 %	3.50 %	3.85 %	0.35 %
3 month	72.06 %	20.37 %	3.39 %	4.01 %	0.15 %
4 month	67.15 %	25.24 %	3.18 %	4.16 %	0.24 %

The proportion of sub-patterns in pattern 2 in 1 month baseline time is shown in Fig. 4 (only one pattern is reported here due to the space restriction). It shows that an overwhelming majority of teens (87.37 %) turns to the stage of intensive stress only after a short period of lower stress, which might be because teens easily feel anxious when facing stress due to their immaturity. Besides, the most prominent sub-pattern is sub-pattern 4, in which the speed of both stress ascent and decline are "fast", which seems like "easy come easy go" when teens' stress get worse. But an important thing to know is there are still 45.6 % teens keep "slow" speed at stress alleviating stage. For these teens, intervention or psychology guidance should be imported early to help them release stress.

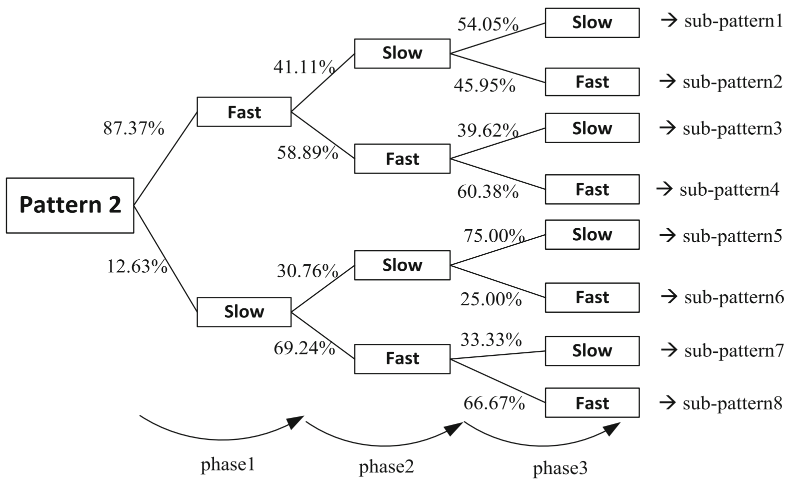


Fig. 4. Detected proportions of 8 sub-patterns in pattern 2

7 Conclusion

Chronic stress can lead to a series of physical and mental health problems. Especially for adolescents, it may result in more serious consequences such as suicide, due to their shortage of psychological endurance and controllability. Therefore, it is particularly necessary to timely detect adolescents' chronic stress and guide them to cope with it. In this study, we propose a framework for chronic stress detection by aggregating individual tweet's stress detection results. We identify five chronic stress change patterns, and give explanations and some advices based on the findings from a user study with 48 students of age 16–17 recruited from a high school. In the future, we plan to implant a personalization model upon the framework to automatically or semi-automatically adapt to different teens' stress detection.

Acknowledgments. The work is supported by National Natural Science Foundation of China (61373022 and 61370023).

References

1. The American Heritage Medical Dictionary. Houghton Mifflin Company (2008)
2. Benson, H., Allen, R.: How much stress is too much? Harvard Bus. Rev. **58**(5), 86–92 (1980)
3. Stress. http://psychology.wikia.com/wiki/Stress
4. Stress contributes to range of chronic diseases, review shows (2007). http://www.sciencedaily.com/releases/2007/10/071009164122.htm
5. Mineur, Y., Prasol, D., Belzung, C.: Agonistic behavior and unpredictable chronic mild stress in mice. Behav. Genet. **33**(5), 513–519 (2003)

6. Psychology today (2014). http://www.psychologytoday.com/blog/web-loneliness/201405/the-loneliness-elliot-rodger
7. Shi, Y., Ruiz, N., Taib, R., Choi, E., Chen, F.: Galvanic skin response (GSR) as an index of cognitive load. In: Proceedings of CHI, pp. 2651–2656 (2007)
8. Hamid, N., Sulaiman, N., Aris, S., Murat, Z., Taib, M.: Evaluation of human stress using EEG power spectrum. In: Proceedings of CSPA, pp. 1–4 (2010)
9. Hosseini, S., Khalilzadeh, M.: Emotional stress recognition system using EEG and psychophysiological signals: using new labelling process of EEG signals in emotional stress state. In: Proceedings of ICBECS, pp. 1–6 (2010)
10. Lu, H., Rabbi, M., Chittaranjan, G., Frauendorfer, D., et al.: Stresssense: detecting stress in unconstrained acoustic environments using smartphones. In: Proceedings of Ubicomp, pp. 351–360 (2012)
11. Bauer, G., Lukowicz, P.: Can smartphones detect stress-related changes in the behaviour of individuals? In: Proceedings of PERCOM Workshop, pp. 423–426 (2012)
12. Park, M., McDonald, D., Cha, M.: Perception differences between the depressed and non-depressed users in Twitter. In: Proceedings of ICWSM, pp. 476–485 (2013)
13. Choudhury, M., Gamon, M., Counts, S., Horvitz, E.: Prediction depression via social media. In: Proceedings of ICWSM, pp. 128–137 (2013)
14. Choudhury, M., Counts, S., Horvitz, E.: Social media as a measurement tool of depression in populations. In: Proceedings of ACM Web Science, pp. 47–56 (2013)
15. Shen, Y.-C., Kuo, T.-T., Yeh, I.-N., Chen, T.-T., Lin, S.-D.: Exploiting temporal information in a two-stage classification framework for content-based depression detection. In: Pei, J., Tseng, V.S., Cao, L., Motoda, H., Xu, G. (eds.) PAKDD 2013. LNCS (LNAI), vol. 7818, pp. 276–288. Springer, Heidelberg (2013). doi:10.1007/978-3-642-37453-1_23
16. Wang, X., Zhang, C., Ji, Y., Sun, L., Wu, L., Bao, Z.: A depression detection model based on sentiment analysis in micro-blog social network. In: Li, J., Cao, L., Wang, C., Tan, K.C., Liu, B., Pei, J., Tseng, V.S. (eds.) PAKDD 2013. LNCS (LNAI), vol. 7867, pp. 201–213. Springer, Heidelberg (2013). doi:10.1007/978-3-642-40319-4_18
17. Xue, Y., Li, Q., Jin, L., Feng, L., Clifton, D.A., Clifford, G.D.: Detecting adolescent psychological pressures from micro-blog. In: Zhang, Y., Yao, G., He, J., Wang, L., Smalheiser, N.R., Yin, X. (eds.) HIS 2014. LNCS, vol. 8423, pp. 83–94. Springer, Heidelberg (2014). doi:10.1007/978-3-319-06269-3_10
18. Lin, H., Jia, J., Guo, Q., Xue, Y., Li, Q., Huang, J., Cai, L., Feng, L.: User-level psychological stress detection from social media using deep neural network. In: Proceedings of MM (2014)
19. Li, Q., Xue, Y., Jia, J., Feng, L.: Helping teenagers relieve psychological pressures: a micro-blog based system. In: Proceedings of EDBT Demo (2014)
20. Healey, J., Picard, R.: Detecting stress during real-world driving tasks using physiological sensors. IEEE Trans. Intell. Trans. Syst. **6**(2), 156–166 (2005)
21. Rigas, G., Goletsis, Y., Fotiadis, D.: Real-time driver's stress event detection. IEEE Trans. Intell. Trans. Syst. **13**(1), 221–234 (2012)
22. Choi, J., Gutierrez-Osuna, R.: Using heart rate monitors to detect mental stress. In: Wearable and Implantable Body Sensor Networks, pp. 219–223 (2009)
23. Sun, F., Kuo, C., Cheng, H., Buthpitiya, S., Collins, P., Griss, M.: Activity-aware mental stress detection using physiological sensors. In: Proceedings of Social Informatics and Telecommunications Engineering, pp. 211–230 (2012)

24. Peng, H., Hu, B., Zheng, F., Fan, D., Zhao, W., Chen, X., Yang, Y., Cai, Q.: A method of identifying chronic stress by EEG. Pers. Ubiquit. Comput. **17**(7), 1341–1347 (2013)
25. Soury, M., Devillers, L.: Stress detection from audio on multiple window analysis size in a public speaking task. In: Proceedings of Affective Computing and Intelligent Interaction, pp. 529–533 (2013)
26. Liao, W., Zhang, W., Zhu, Z., Ji, Q.: A real-time human stress monitoring system using dynamic Bayesian network. In: Proceedings of CVPR (2005)
27. Mokhayeri, F., Akbarzadeh-T, M.-R.: Mentail stress detection based on soft computing techniques. In: Bioinformatics and Biomedicine, pp. 430–433 (2011)
28. Bousefsaf, F., Maaoui, C., Pruski, A.: Remote assessment of the heart rate variability to detect mental stress. In: Proceedings of Pervasive Computing Technologies for Healthcare Workshops, pp. 348–351 (2013)
29. Kurniawan, H., Maslov, A., Pechenizkiy, M.: Stress detection from speech and galvanic skin response signals. In: Proceedings of CBMS, pp. 209–214 (2013)
30. Cohen, S., Kamarck, T., Mermelstein, R.: A global measure of perceived stress. J. Health Soc. Behav., 385–396 (1983)
31. Cheng, T., Wu, J., Chong, M., Williams, P.: Internal consistency and factor structure of the Chinese health questionnaire. Acta Psychiatr. Scand. **82**(4), 304–308 (1990)
32. Contrada, R.J.: The Handbook of Stress Science. Springer Publishing Company. LLC, New York (2011)