

Monitoring Stress Arousal in the Wild

Wearable sensors can provide continuous biosignal measurements, which systems can use to infer psychological stress arousal. The authors deploy such sensors to monitor a public speaker, an on-stage musician, an Olympic ski jumper, and people during everyday life, quantifying stress arousal in varying contexts.

Many taxing situations of everyday life can cause negative arousal—also known as *stress arousal*. During such situations, our hearts pound, we become short-winded, and we start sweating. Professional musicians, athletes, and many others regularly experience stress arousal as part of their professional activities. Stress arousal can impair our ability to perform and increase the probability of making mistakes. Furthermore, repeatedly having a negative experience during stressful situations can affect behavior and well-being, which can lead to situation avoidance and curtail professional careers.

Monitoring stress arousal in natural environments is challenging, because no gold standard exists for measuring it; responses to stressors can vary across individuals, situations, and stressor types; and stressful situations in daily life can occur at random—in different places and with varying duration and intensity. To measure stress arousal, researchers often use self-reports that qualify personal stress perception. However, self-reporting is a subjective measure. Furthermore, its practical use in everyday life is limited, because respondents easily forget relevant arousal events, and active engagement during reporting

interferes with other daily activities and regular behavior.

Recent research shows that wearable systems can monitor stress-related biosignals, and selected analysis methods can reveal objective measures of an individual's stress arousal outside of labs. As a first step toward developing stress-arousal assistant systems, we present selected studies deploying wearable monitoring systems, deriving information about stressors and identifying existing challenges in this area.

Measuring the Intangible

Stress-arousal monitoring can use various human biosignals. Researchers have used sensors attached to or in close proximity to the body (for more information, see the “On-Body Sensing Modalities for Arousal Monitoring” sidebar). However, not all modalities are equally applicable in daily life: miniaturization and comfort are key, but sensitivity to body motion can mask stress arousal in sensor signals. For example, your heart rate can increase in a stressful situation or when climbing stairs. Subsequently, biosignal monitoring and analysis approaches must disentangle physical activity from subtle changes pertaining to psychological stressors.

Only a few researchers have started to address the stress-arousal monitoring challenge. (The “Assessing Stress Arousal in the Wild” sidebar presents related work.) Major considerations include the monitoring system's size, weight, and battery runtime, as well as its reliability

Martin Kusserow
ETH Zurich

Oliver Amft
TU Eindhoven

Gerhard Tröster
ETH Zurich

On-Body Sensing Modalities for Arousal Monitoring

The body's stress-arousal reaction involves different biological systems that generate biosignals. Biosignals can be measured through a variety of wearable sensing modalities. Table A summarizes noninvasive wearable biosignal sensing modalities, typical measurements that can be extracted with these sensing modalities, and their typical on-body sensing sites.¹⁻⁷

Some measurements, such as heart rate, can be extracted from several sensing modalities, but their placement must be considered. Photoplethysmograms (PPGs) placed on the finger would limit the natural use of hands and interfere with some activities of daily living. Similarly, electrodes placed in the face to measure facial muscle activity alter the user's natural appearance.

Using additional accessories, for example, glasses containing electrodes for an electrooculogram (EOG), a cap or headband with electrodes for an electroencephalogram (EEG) or near-infrared spectroscopy (NIRS), or earrings with PPGs, can alleviate appearance issues. In addition, researchers have combined biosignal sensing modalities and incorporated other on-body sensing modalities, such as body motion in multimodal sensor

systems (for more information, see the "Assessing Stress-Arousal in the Wild" sidebar).

REFERENCES

1. M. Myrtek, *Heart and Emotion: Ambulatory Monitoring Studies in Everyday Life*, Hogrefe & Huber Publishers, 2004.
2. W. Boucsein, *Electrodermal Activity*, W. Boucsein, ed. Springer, 2011.
3. J.L. Andreassi, *Psychophysiology: Human Behavior and Physiological Responses, 5th ed.*, Lawrence Erlbaum Associates, 2007.
4. G.H. Willemsen et al., "Ambulatory Monitoring of the Impedance Cardiogram," *Psychophysiology*, vol. 33, no. 2, 1996, pp. 184–193.
5. F. Wilhelm, W. Roth, and M. Sackner, "The LifeShirt," *Behavior Modification*, vol. 27, no. 5, 2003, pp. 671–691.
6. M. Tanida, M. Katsuyama, and K. Sakatani, "Relation between Mental Stress-Induced Prefrontal Cortex Activity and Skin Conditions: A Near-Infrared Spectroscopy Study," *Brain Research*, vol. 1184, 2007, pp. 210–216.
7. J. Allen, "Photoplethysmography and its Application in Clinical Physiological Measurement," *Physiological Measurement*, vol. 28, no. 3, 2007, pp. R1–R39.

TABLE A

An overview of wearable biosignal sensing modalities, typical measurements that can be extracted with these sensing modalities, and their typical on-body sensing sites.

Sensing modality	Typical measurement	Sensing site
Electrocardiogram (ECG) ¹	Heart rate (variability) and ECG-waveform segments	Thorax
Electrodermal activity (EDA) ²	Skin sweat level and fluctuations	Palm, foot, and wrist
Electroencephalogram (EEG) ³	Brain waves (alpha, beta, and theta)	Scalp
Electromyogram (EMG) ³	Muscle tension, facial expressions, and eye blink rate	Upper back and face
Electrooculogram (EOG) ³	Eye movement and blink rate	Near the eye
Impedance cardiogram (ICG) ⁴	Heart rate, heart stroke volume, and pre-ejection period	Thorax and neck
Inductive plethysmography (RIP) ⁵	Respiration rate and tidal volume	Thorax
Near-infrared spectroscopy (NIRS) ⁶	Blood oxygen saturation	Scalp
Photoplethysmogram (PPG) ⁷	Heart rate, blood oxygen saturation, and blood pressure	Finger and ear
Sphygmomanometer ³	Blood pressure	Upper arm and finger

and robustness when used during daily life activities. In addition, researchers are investigating algorithmic solutions to detect and quantify stress arousal from continuous sensor data while accounting for the masking effect of body motion. Monitoring systems should also provide activity and context information that can be associated with

sensor-estimated stress arousal, which could help qualify and interpret stressors. For example, working at the office might generate different stress-arousal patterns than commuting, competing in a sporting event, or performing on stage.

Stress-arousal assistant systems can help assess and counteract the downsides of stress arousal. An assistant

system would continuously monitor a user's stress-arousal state and support the user if stress arousal started to deteriorate his or her performance or well-being. Although reliable and robust wearable sensor systems have become feasible, we have yet to develop methodological approaches for understanding stress arousal.

Assessing Stress Arousal in the Wild

Researchers in behavioral sciences often use self-reporting of participants' experiences and perception. The *day reconstruction method* assesses activities, stressful events, and other affective experiences during the day in a retrospective manner.¹ Similarly, the *daily hassles and uplifts scale* assesses the experienced positive and negative events during the day.² In contrast, the *experience sampling method* asks users questions (usually about perceived conditions) at random intervals during the day.³

In addition to self-reports, researchers use wearable sensors to monitor body motion and stress-arousal-related biosignals. However, only a few works have investigated wearable sensing in natural settings. Among the few studies, most faced problems regarding sensor system reliability and robustness, a lack of algorithmic solutions to detect and quantify stressful episodes from sensor signals, and accounting for the influence of body motion.

Juha Pärkkä and his colleagues explored the relationship between biosignal, environmental, and psychological measures in people suffering from work overload.⁴ Rosalind Picard and her colleagues developed a device that can monitor electrodermal activity (EDA) during daily living.⁵ Aiming at distinguishing high and low arousal states during everyday life, Jennifer Healey and her colleagues developed a sensing system combining EDA, heart rate, and a mobile phone to collect users' self-reports.⁶ Kurt Plarre and his colleagues aimed to distinguish stress from no-stress episodes during sedentary activities of daily living using five biosignals.⁷ Michael Myrtek and his colleagues developed the additional heart rate (AHR) algorithm to detect onsets of emotional events by jointly analyzing heart

rate and body acceleration during daily living,⁸ which we also used in our work.

REFERENCES

1. D. Kahneman et al., "A Survey Method for Characterizing Daily Life Experience: The Day Reconstruction Method," *Science*, vol. 306, no. 5702, 2004, pp. 1776–1780.
2. A. DeLongis, S. Folkman, and R.S. Lazarus, "The Impact of Daily Stress on Health and Mood: Psychological and Social Resources as Mediators," *J. Personality and Social Psychology*, vol. 54, no. 3, 1988, pp. 486–495.
3. R. Larson and M. Csikszentmihalyi, "The Experience Sampling Method," *New Directions for Methodology of Social & Behavioral Science*, vol. 15, 1983, pp. 41–56.
4. J. Pärkkä et al., "Relationship of Psychological and Physiological Variables in Long-Term Self-Monitored Data During Work Ability Rehabilitation Program," *IEEE Trans. Information Technology in Biomedicine*, vol. 13, no. 2, 2009, pp. 141–151.
5. R. Picard and J. Scheirer, "The Galvactivator: A Glove that Senses and Communicates Skin Conductivity," *Proc. 9th Int'l Conf. Human-Computer Interaction*, Lawrence Erlbaum Associates, 2001, pp. 1538–1542.
6. J. Healey et al., "Out of the Lab and into the Fray: Towards Modeling Emotion in Everyday Life," *Proc. 8th Int'l Conf. Pervasive Computing*, LNCS 6030, Springer, 2010, pp. 156–173.
7. K. Plarre et al., "Continuous Inference of Psychological Stress from Sensory Measurements Collected in the Natural Environment," *Proc. 10th Int'l Conf. Information Processing in Sensor Networks (IPSN 11)*, IEEE, 2011, pp. 97–108.
8. M. Myrtek, *Heart and Emotion: Ambulatory Monitoring Studies in Everyday Life*, Hogrefe & Huber Publishers, 2004.

In addition to researching everyday-life stress-arousal conditions, our work builds on investigations in natural stressful situation with known stressors—that is, context-specific conditions. As we demonstrate, developing wearable systems that can identify context-specific conditions moves us closer to stress-arousal assistance in everyday life.

Stress-Arousal Monitoring Conditions

In lab-based monitoring, researchers can monitor the type and timing (onset, duration, and frequency) of a stressor, collect instant self-reports, and record sensor data under standardized and

repeatable conditions. Outside of a lab, stressful situations naturally unfold without options to apply lab-like control.

When moving to daily-life monitoring, our approach has been to gradually release controlled conditions used in lab-based investigations, where stressors are known and controllable. We observed that various natural environments can serve as intermediate steps, providing known stressors and activities. For example, giving a public talk is a known stressful condition. We refer to such conditions as *context-specific monitoring*, filling a gap between purely lab-based and daily-life conditions. Figure 1 illustrates the different monitoring conditions.

In context-specific monitoring, the stressor and its timing typically can't be controlled. However, knowing the stressor, context, and activities involved lets us deploy targeted wearable monitoring systems and apply specific analysis techniques. In context-specific conditions, we investigated which physiological signals can provide relevant psychological indicators. We also studied the extent to which body-motion noise impairs this identification.

In contrast to context-specific conditions, monitoring in daily-life conditions must deal with different stressors simultaneously. Moreover, activities and contexts vary more widely in this condition.

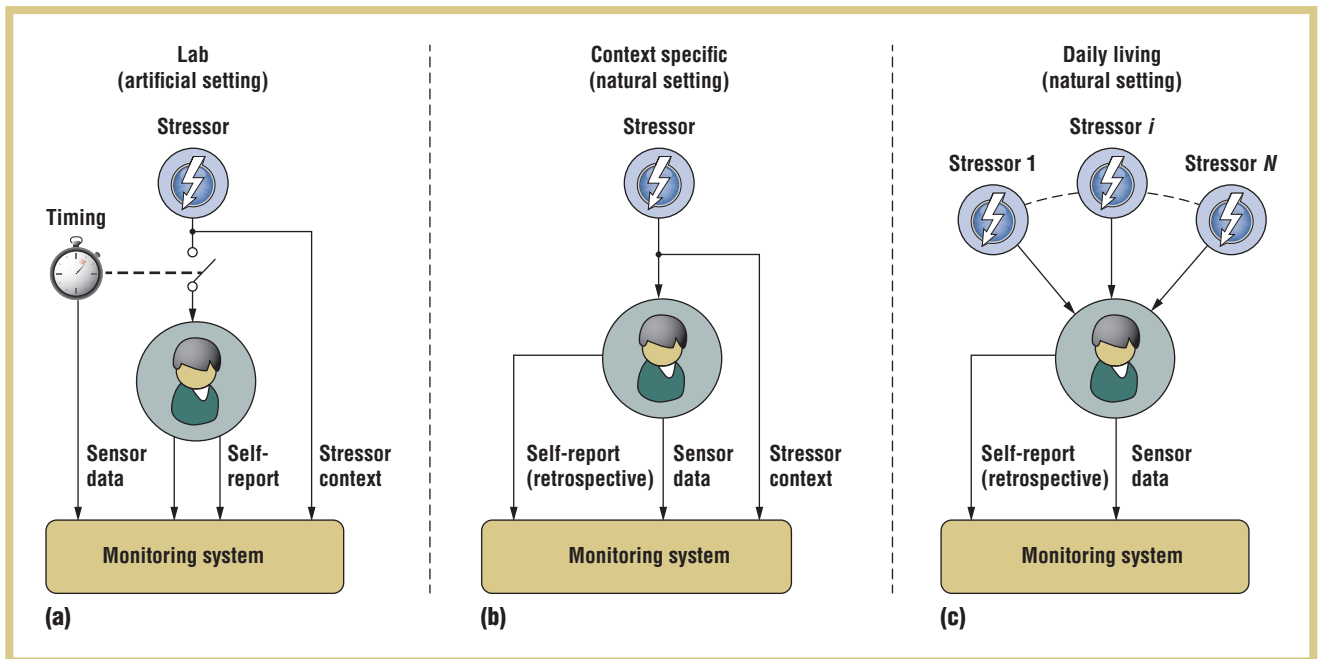


Figure 1. Stress-arousal monitoring conditions. (a) In lab-based monitoring, researchers control the stressor type and timing (onset, duration, and frequency) and receive instant subject reports and sensor data. In contrast, (b) context-specific and (c) daily-life monitoring use stressors embedded in natural settings, with constraints on sensor data quality and the details of the monitored information.

Case Studies

Here, we present four studies illustrating the benefits of wearable monitoring and analysis in natural settings under context-specific and daily-life conditions.

Monitoring a Public Speaker

Speaking in front of an audience is a stressful situation for many people and can impair oral fluency and information recall. To regulate stress arousal and improve the presentation experience, we introduced a *talk assistant*.¹ The talk assistant detects stress arousal and provides personalized feedback, conveyed through the speaker's on-body system or an external infrastructure (such as displays near the speaker). Different types of relaxation feedback have been proposed in the literature, such as simple reminders of breathing or speaking styles. Figure 2a shows our context-specific monitoring of a speaker.

Our system can be worn during public talks without interfering with the

speaker or being noticed by the audience. The sensing system comprised a wireless heart rate monitor (HRM) and a belt-integrated computer, called the QBIC. In addition, we developed a miniature sensor node that measures electrodermal activity (EDA), acceleration, and temperature. The EDA measurement circuit comprised a Wheatstone bridge and a microcontroller to calculate skin conductance values. The sensor node features a miniature form factor of $21 \times 17 \times 6$ millimeters and weighs 15 grams, including the electrodes and battery.

Figure 2b shows the wearable sensor system signals during a PhD student's presentation for approximately 20 researchers. These four signals measure heart rate, skin conductance level at the wrist, total acceleration dynamics of the wrist, and total acceleration dynamics of the thigh. As the top signal shows, the speaker's heart rate immediately increased at the start of the talk and decreased at the start of the Q&A period. In contrast, the skin

conductance level steadily increased during the talk and recovered after the Q&A period. We found this pattern in additional study participants, confirming the findings illustrated here. For this example, we concluded that heart rate and EDA could complement each other, as they reacted differently to the talk and Q&A period.

Because we targeted speaker support during the talk, we investigated relevant heart activity features that could be used to adapt speaker feedback.¹ We monitored five PhD students during real conference talks and found that their heart rates significantly increased, consistently, between the talk and the pre- and post-talk periods. Interestingly, in this natural setting, heart rate variability (HRV) features—often reported to indicate stress arousal in lab studies—showed little significance for some speakers. HRV features are probably more sensitive to slight body motion than heart rate. The maximum heart rate occurred within the first

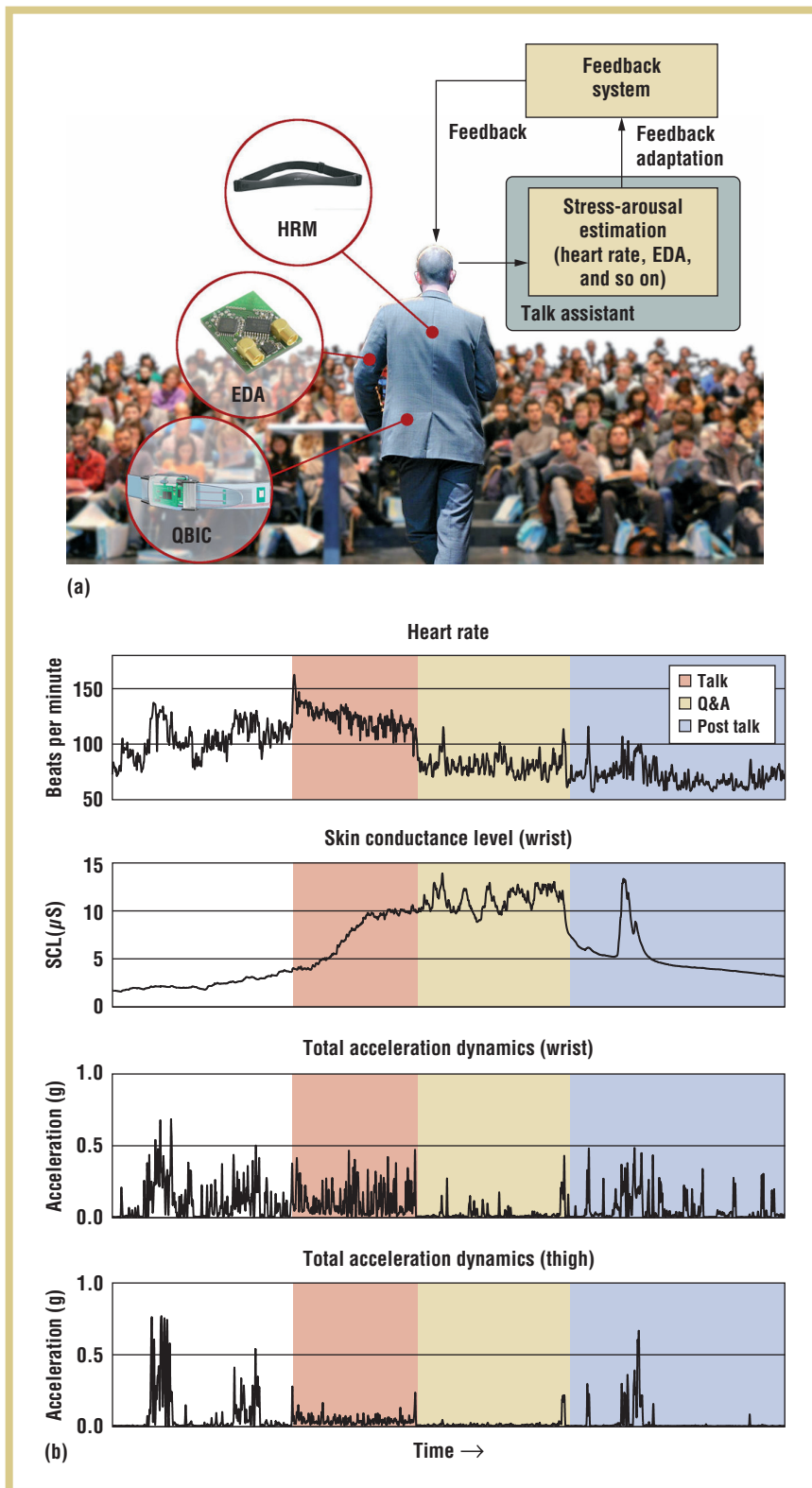


Figure 2. The wearable talk assistant, which helps manage stress arousal during public speaking. (a) Context-specific monitoring of a speaker during a presentation. The wireless sensing system comprises a heart rate monitor (HRM), an electrodermal activity sensor node (EDA), and the Q-belt integrated computer (QBIC). (b) An example of a talk recording showing the heart rate, skin conductance level (SCL) measured at the wrist, and the total acceleration dynamics of both the wrist and thigh.

A talk assistant system could capitalize on talk-phase information (confrontation and adaptation) and the heart rate to trigger possible relaxation feedback to the speaker. In addition to automatic stress-arousal estimation, the speaker should have the option to manually adjust relaxation feedback depending on the expected stress-arousal level. To extend our talk assistant system, we plan to incorporate EDA and add other modalities (such as voice and body language) known to indicate talk performance.

Monitoring a Musician on Stage

A musical performance requires finely tuned vocal or instrumental skills that can be affected by stress arousal—often referred to in the performing arts as *stage fright*. Options for assessing stress arousal during an on-stage performance have been limited to retrospective self-report and expert observation. Using sensor-based measurements to complement subjective impressions can help us better understand how stage fright can affect performance quality so we can develop coping strategies.

In this context-specific condition, we developed a sensor system for monitoring and analyzing a professional cellist during performances.² The system comprised acceleration sensors and an electrocardiogram (ECG) recorder. We attached the acceleration sensors to both wrists and placed the ECG recorder on the cellist's chest (see Figure 3a).

1.5 minutes, and recovery to the pre-talk heart rate took up to 11 minutes, suggesting two stress-arousal phases

(confrontation and adaptation). Heart rate classification discriminated the two phases.

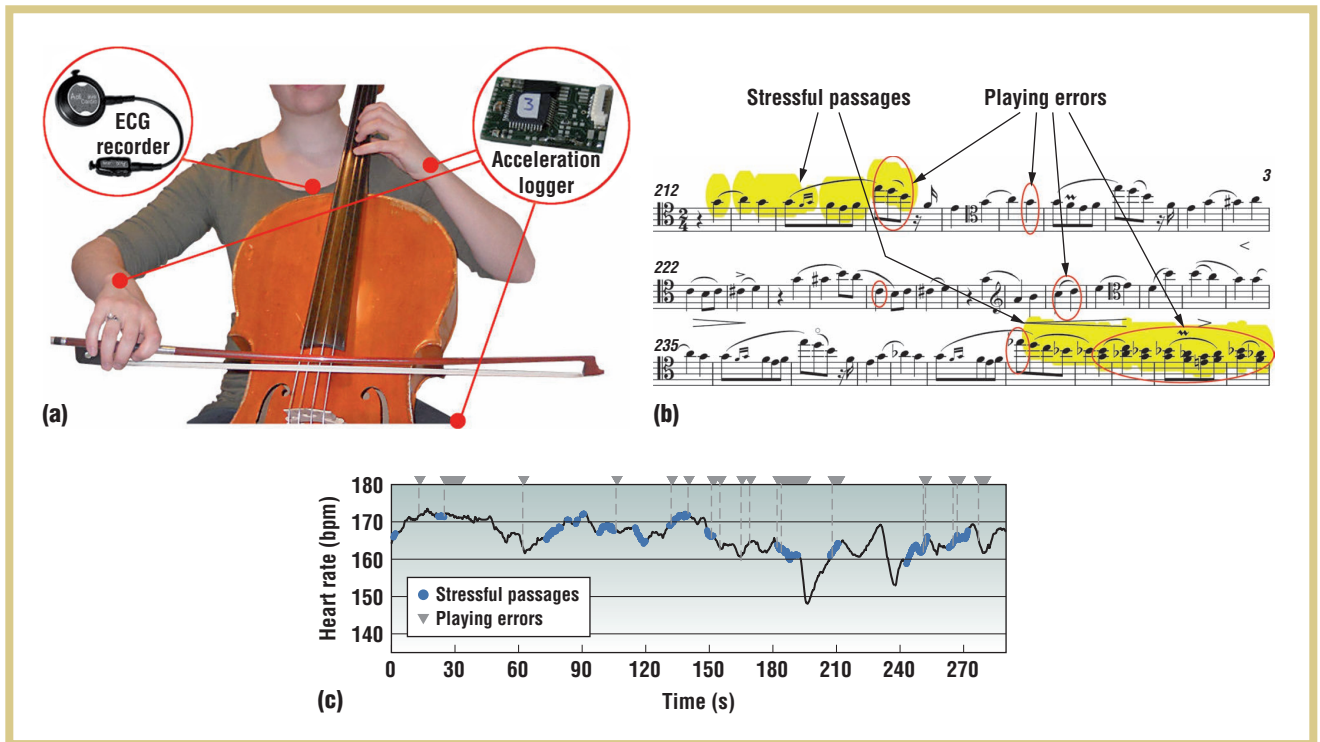


Figure 3. Context-specific stress-arousal monitoring of a cellist on stage. (a) The wearable sensor system: acceleration loggers, an ECG recorder, and their positioning on the cellist’s body. (b) An excerpt from a score showing the stressful passages, as annotated by the cellist, and our annotations of technical playing errors. (c) The heart rate signal of the cellist during one performance together with stressful passages, as annotated by the cellist in the score, and technical playing errors.

Using our wearable system, we monitored the cellist during three on-stage performances in front of an audience of approximately 20 music students and professors. Across multiple performances, we measured significant trends in heart rate and body motion. At the same time, the subjective perception of stage fright and the number of technical playing errors decreased. In particular, the sensors detected a 6 percent increase in bowing arm acceleration and a 2 percent decrease in heart rate. The increase in bowing arm acceleration could be interpreted as a release in muscle freezing (muscle relaxation). Muscle freezing can slow down fine motor skills during the performance. This conjecture was further supported by the fact that the cellist played the piece faster across multiple performances. The cellist reported a decrease in perceived stage fright—a trend reflected in the heart rate measurements. During the first

performance, technical playing errors occurred more frequently and were more likely to occur during stressful passages. The error rate dropped significantly and was equally likely during stressful and other passages for the last performance.

Professors and students of Zurich University of the Arts stated that our approach provided new assistance for identifying stage fright, which they otherwise couldn’t assess. In particular, it helped track subtle changes in acceleration dynamics and heart rate across multiple performances in relation to performance quality and stressful passages. In this context-specific monitoring condition, a stage-fright assistant system could not only capture heart rate and body motion but also additional information about technical playing errors and stressful passages, as indicated by the musician. Using this information, individual stage-fright

perception and actual performance quality could be related to objective sensor measures.

Figure 3b shows an example of the cellist’s annotation of stressful passages and our annotation of technical playing errors. Figure 3c shows their mapping into the heart rate signal during performance. In the future, we plan to use wearable systems to make musicians and other performing artists aware of their stage fright and help them overcome it.

Monitoring an Olympic Champion

Ski jumping competitions are stressful. In ski jumping, an optimal mental state is considered critical to top performance. For example, stress arousal impairs finely tuned body perception required for precise timing of high-speed motion sequences at takeoff. Assessing and regulating stress arousal is thus essential for success. However, no

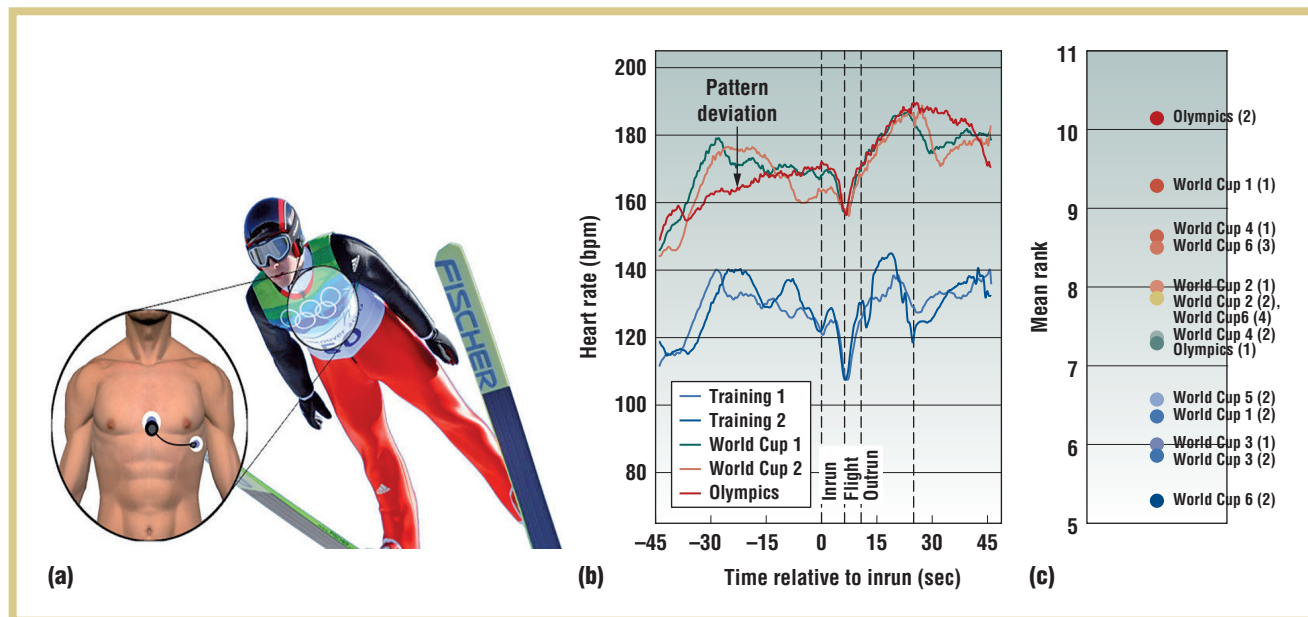


Figure 4. Context-specific wearable monitoring of stress arousal in professional ski jumping. (a) An electrocardiogram (ECG) recorder and its placement on the athlete's body. (b) Typical heart rate patterns recorded during trainings and competitions, including the 2010 Olympics. The pattern of the Olympics jump deviated from the standard competition pattern before jumping during the athlete's pre-performance routine when stress-arousal regulation was impaired. (c) Ranking of heart rate patterns during pre-performance routines in competitions. Higher mean ranks indicate lower similarity (the jump number appears in parentheses).

current solutions objectively measure stress arousal in ski jumping and establish an understanding of its characteristics during competitions.

We introduced context-specific monitoring in professional ski jumping for the first time during competitions.³ We developed a heart activity analysis approach for the 2010 Olympic champion, Simon Ammann. The wearable system was a miniature and lightweight ECG recorder with an integrated accelerometer, attached to the athlete's chest. The acceleration signal provided the segmentation information of jumps and jumping phases. Figure 4a depicts the ECG recorder and its attachment.

Our context-specific analysis procedure had two parts. First, we analyzed the heart rate during three different competitive situations (training, qualification, and competition) with respect to the ski-jumping phases—inrun, flight, and outrun. Second, we analyzed the heart rate pattern during

pre-performance routines before jumping in competitions when the athlete regulated his arousal.

The coaches considered heart rate patterns that are reproducible across competitions as an indicator of an effective pre-performance routine. For heart rate pattern analysis, we used a dynamic time-warping-based similarity measure and ranking scheme. Using our sensing approach, Ammann recorded 99 hours of data, including 37 hill jumps in World Cup competitions and the 2010 Winter Olympics.

We found that stress arousal based on heart rate increased significantly with the competitiveness of the jumping situation, from training (118 beats per minute), to qualification (152 bpm), to competition (168 bpm). The athlete's self-report of stress-arousal level confirmed this trend. Independent of the jump situation, we observed reproducible heart rate patterns during jumping: the heart rate dropped

during inrun until takeoff, increased during the flight, and peaked at the end of the outrun.

Figure 4b depicts the heart rate pattern during jumping and compares heart rate level during training and competitions. Ammann ranked first for almost all competitions, so we concluded that this pattern during jumping reflected his optimal stress-arousal state.

In addition, the analysis of heart rate patterns revealed additional information related to stress arousal—that is, deviations in pre-performance routines. Our procedure ranked the heart rate pattern of the pre-performance routine before the final jump of the Olympics as most dissimilar (this heart rate pattern is depicted in Figure 4b, too). For this particular jump, the athlete reported extreme levels of stress arousal and difficulties in regulating it before taking the gate.

The athlete and his coaches reported that the quantification of stress arousal

by measuring heart rate and its patterns helped compare the subjective perception to objective measurements across competitions throughout the season. After each competition, we provided Ammann and his coaches with the heart rate measurements and patterns—see, for example, the visualization shown in Figure 4b. The coaches considered our wearable stress-arousal assistance a valuable instrument for complementing technical skills training in the future, especially for developing personal pre-performance routines for newcomer athletes.

In the future, we plan to continue our collaboration in ski jumping and extend the heart rate analysis by incorporating expert ratings of physical performance parameters, such as timing at takeoff.

Monitoring Daily-Life Activities

When approaching daily-life conditions, wearable monitoring becomes substantially more difficult because unpredictable situations and encounters can arouse stress. The frequency, duration, intensity, and personal context of stress arousal are variable, and physical activity can create noise in stress-arousal patterns in biosignals.

We built a multimodal framework incorporating activity-context information to estimate stress-arousal phases in daily life. A stress-arousal phase is described by onset, duration, and intensity. Here, we overview the approach used to investigate stress arousal. We don't analyze accuracy here, because reference information on stress arousal is hard to obtain in free living. Instead, we show how stress arousal can be filtered using daily activities.

Our framework for stress-arousal estimation comprises the detection of arousal onsets (activations) by measuring heart rate and body acceleration and subsequently estimating phase duration and intensity. The detection of activations is based on a refined version of the additional heart

rate (AHR) algorithm, which was developed and evaluated by psychologists as an indicator of general psychological arousal.⁴ The AHR algorithm fuses heart rate and body-acceleration information to identify those minutes in which heart rate exceeds the level estimated from physical activity intensity. However, the original AHR algorithm used physical activity intensity only, so detection is susceptible to other influences not related to stress arousal, such as body-posture transitions.

We implemented a filtering scheme incorporating a set of basic activity classes, called *primitives* (including “sit,” “stand,” and “walk”) to eliminate activations influenced by activity transitions. The rationale behind our approach is that activations with constant activity context as represented by the set of primitives are more likely to be of psychological origin than those where the activity context changes during the minute of activation.

Finally, we introduced a segmentation algorithm using the AHR signal and an activation-specific recovery detector to estimate the stress-arousal phase duration and intensity. Our developed procedure is depicted in Figure 5a.

We tested our approach with four PhD students during 182 hours of their daily life. The monitoring system comprised an HRM, two wireless acceleration sensor nodes attached to the chest and thigh, and the QBIC. Figure 5b shows the on-body monitoring system and sensor placement. The participants kept a diary of nonoverlapping daily activities (such as eating, working, and using public transport) and completed mood-state questionnaires during the day—in particular, as soon as possible after they perceived a stress-arousal situation.

Using our phase-estimation procedure, we obtained different individual and daily-activity-specific stress-arousal characteristics, although both the distribution of daily activities and

the amount of physical activity were comparable across participants. On average, arousal-phase duration was between two and five minutes, and all participants showed the highest arousal intensity in the office environment. Some questionnaires coincided with detected arousal phases, suggesting that some salient situations were instantly reported. Most questionnaires were completed randomly during the day, and we concluded that these reports weren't related to estimated stress-arousal phases.

Figure 5c shows the estimated probabilities $P(A|R)$ of being in an arousal phase A during a daily activity R. $P(A|R)$ denotes the ratio between total time of an arousal phase A during daily activity R and the total duration of the respective daily routine R. As a prominent example, the estimated $P(A|R)$ was highest for participant 4 during *eating*. From the activity diary of participant 4, we learned that mealtimes were variable and coincided with *work*, *transport*, or *conversation*. Thus, we concluded that engagement in multiple tasks at once was related to higher estimated stress-arousal probability for this participant.

Our study has demonstrated that daily-life monitoring is technically feasible. However, the number of unpredictable stressors and activity contexts in daily life confirmed that several sensing modalities, estimation algorithms, context information, and questionnaire assessments must be combined to relate biosignal patterns and stress-arousal contexts in daily-life conditions. Nonetheless, using only two sensing modalities and an improved context-aware AHR algorithm, we were able to quantify phase onset, duration, and intensity. Self-reported mood and daily activity in close proximity of detected phases let us relate the detections to plausible stress-arousal contexts.

Our context-aware adaptation of the original AHR algorithm is a first

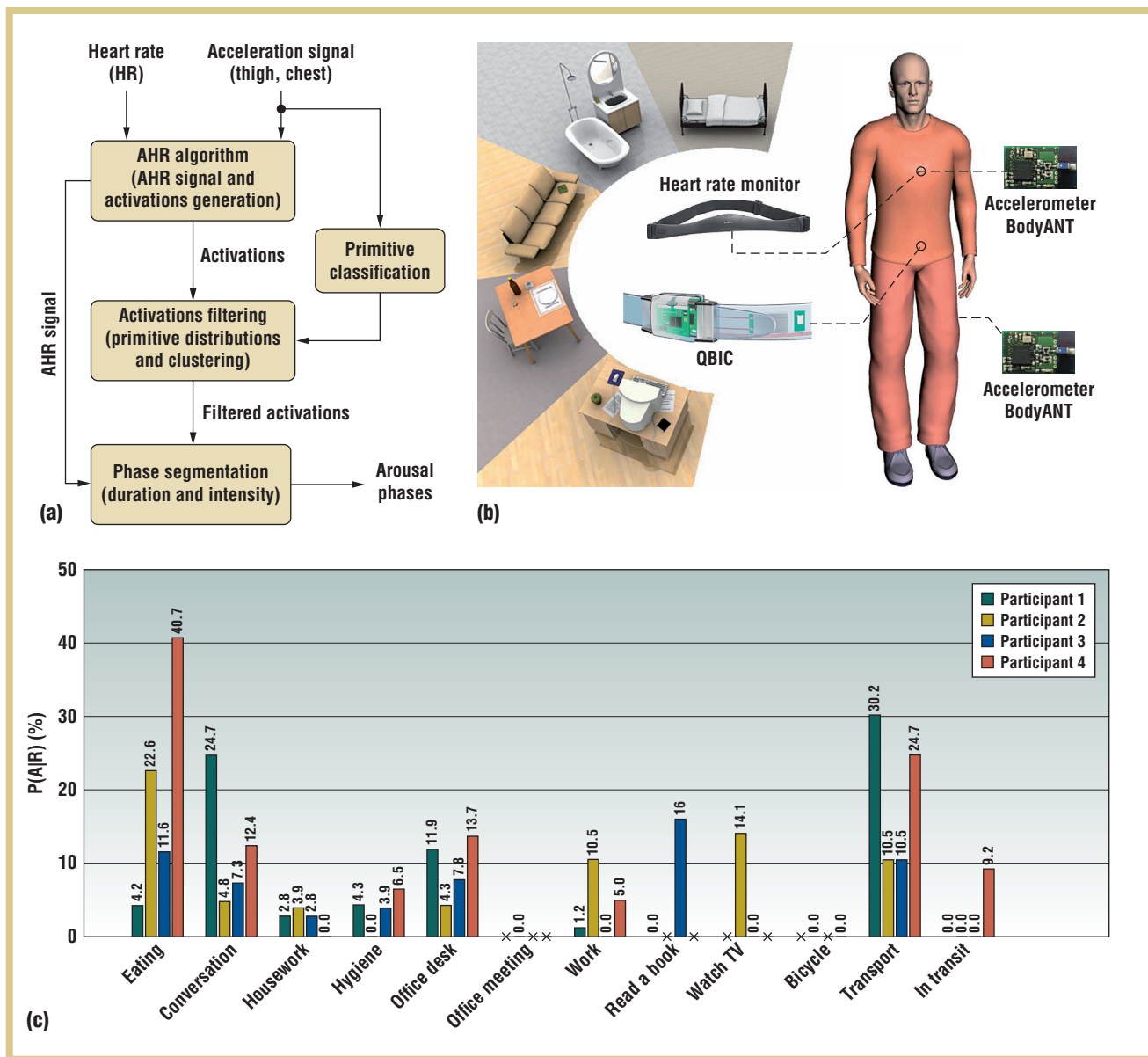


Figure 5. Monitoring stress-arousal phases in daily-life conditions. (a) A schematic of the stress-arousal phase estimation, including the detection of activations, their filtering, and estimation of duration and intensity. (b) The wearable monitoring system and sensor placement for day-long recording: the heart rate monitor (HRM) chest belt, wireless acceleration sensors (BodyANT), and Q-belt integrated computer (QBIC). (c) The probability $P(A|R)$ of being in an arousal A phase during a daily activity R based on the estimated stress-arousal phases. (Daily activities that were not recorded for a participant are marked with "x.")

step toward considering diverse physical activity categories in relation to biosignal patterns, instead of naively omitting measurements affected by physical activity. This approach is essential to clarify the extent to which type and intensity of physical activity

actually influence stress-arousal monitoring. A stress-arousal assistant can thus adapt to personal activity characteristics related to stress arousal. In the future, we plan to develop arousal models using our detection approach and incorporate

temporal as well as contextual information of consecutive stress-arousal phases.

Lessons Learned

Although estimating stress arousal in the wild is an open technical challenge,

our approaches revealed interesting opportunities for assistant systems. Our work showed how context-specific conditions with known stressors can help research take gradual steps toward daily-life monitoring conditions. We considered the analysis of context-specific short-term stress arousal as a suitable approach to relate physiological responses to specific physical activities and stressful situations in natural environments. The analysis of accumulated short-term stress arousal could contribute to understanding long-term stress arousal, such as work overload and burnout.

From our context-specific studies, we learned that heart rate features can be related to stress arousal, even in changing physical activity contexts and varying stressor types. Our work with ski jumpers showed that combining stress-arousal estimation based on heart rate with the athlete's perception can help to determine and potentially even improve performance. Additional information related to stress arousal, such as self-reporting and performance ratings, can be used to complement a wearable sensor-based assistant system.

However, wearable systems don't need to be overly complex or combine many sensor modalities, especially if the measurement and stressor contexts are known. Similarly useful context-specific monitoring systems could be realized for many other applications. This successful monitoring will eventually let researchers develop assistant systems for various situations. Assistance could be provided by visualizing a history of stress-arousal events or by giving feedback before and during the stressful situation. For example, Pedro Sanches and his colleagues investigated different interface designs to visualize stress arousal.⁵ Such feedback could help in developing self-awareness for stress-arousal situations and personal coping styles.

In daily-life monitoring conditions with unpredictable stressors,



Martin Kusserow was a senior researcher in the Wearable Computing Lab at ETH Zurich, Switzerland, when he wrote this article. He's now with Schindler Elevator Ltd. in Switzerland. His research interests include wearable computing, physiological monitoring, sports, and real-world sensing. Kusserow has a PhD in information technology and electrical engineering from ETH Zurich. He's a member of IEEE. Contact him at martin.kusserow@alumni.ethz.ch.



Oliver Amft is an assistant professor at TU Eindhoven, leading the ACTLab research group, and he's a senior research advisor at the Wearable Computing Lab at ETH Zurich. His research interests include ubiquitous sensing, activity pattern recognition, and human behavior inference. Amft has a PhD in information technology and electrical engineering from ETH Zurich. He's a member of IEEE. Contact him at amft@ieee.org.



Gerhard Tröster is a professor and head of the Wearable Computing Lab at ETH Zurich, Switzerland. His research interests include wearable computing for healthcare, and production, smart textiles, sensor networks, and electronic packaging. Tröster has PhD in electrical engineering from the Technical University Darmstadt. He's a senior member of IEEE. Contact him at troester@ife.ee.ethz.ch.

multimodal measurements that capture body motion and heart activity seem essential. In particular, we conclude that multimodal measurements can resolve ambiguities in biosignal patterns caused by parallel stress arousal and physical activity transitions. Moreover, context-related interpretations can help us interpret stress-arousal events.

The promising results shown here warrant further research. Based on these results, we intend to develop models that could describe stress arousal in daily life. Nevertheless, expertise from psychologists and other professionals is essential to realize and advance stress-arousal assistance technologies. ■

ACKNOWLEDGMENTS

We thank all project collaborators and study participants for dedicating their expertise and time.

REFERENCES

1. M. Kusserow, O. Amft, and G. Tröster, "Analysis of Heart Stress Response for a Public Talk Assistant System," *Proc. European Conf. Ambient Intelligence*, Springer, 2008, pp. 326–342.
2. M. Kusserow et al., "Monitoring Stage Fright Outside the Laboratory: An Example in a Professional Musician Using Wearable Sensors," *Medical Problems of Performing Artists*, vol. 27, no. 1, 2012, pp. 21–30.
3. M. Kusserow et al., "Arousal Pattern Analysis of an Olympic Champion in Ski Jumping," *Sports Technology*, vol. 3, no. 3, 2011, pp. 192–203.
4. M. Myrtek, *Heart and Emotion: Ambulatory Monitoring Studies in Everyday Life*, Hogrefe & Huber Publishers, 2004.
5. P. Sanches et al., "Mind the Body! Designing a Mobile Stress Management Application Encouraging Personal Reflection," *Proc. 8th ACM Conf. Designing Interactive Systems*, ACM, 2010, pp. 47–56.



Selected CS articles and columns are also available for free at <http://ComputingNow.computer.org>.