Insights on Modelling Physiological, Appraisal, and Affective Indicators of Stress using Audio Features

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Abstract—Stress is a major threat to well-being that manifests in a variety of physiological and mental symptoms. Utilising speech samples collected while the subject is undergoing an induced stress episode has recently shown promising results for the automatic characterisation of individual stress responses. In this work, we introduce new findings that shed light onto whether speech signals are suited to model physiological biomarkers, as obtained via cortisol measurements, or self-assessed appraisal and affect measurements. Our results show that different indicators impact acoustic features in a diverse way, but that their complimentary information can nevertheless be effectively harnessed by a multi-tasking architecture to improve prediction performance for all of them.

I. INTRODUCTION

Stress is a major public health threat afflicting millions around the world and posing a risk to their physical and mental well-being. A stress episode is characterised by the secretion of several hormones, of which cortisol is the most prominent [1]. The release of such hormones is known to alter other physiological responses, e.g., heart rate [2], which in turn affect speech, particularly during psychosocial stress [3]. Consequently, speech signals include valuable information on well-being [4], stress [5, 6], states of emotional arousal [7], and co-occurring conditions like anxiety [8].

While the activation of the hypothalamus–pituitary–adrenal (HPA) axis and resulting hormonal response provide a satisfactory characterisation of stress from a psychoneuroendocrinological perspective, it is also desirable to characterise stress episodes from a psychological perspective [9]. This adopts the viewpoint that stress can be thought of as “a particular relationship between the person and the environment that is appraised by the person as taxing or exceeding his or her resources and endangering his or her well-being” [10]. Psychosocial stress can therefore be conceptualised as the result of a cognitive appraisal process resulting in an emotional, physiological, and behavioural stress response [11]. In lab conditions, this process can be accordingly measured through self-assessed questionnaires, such as the Positive Appraisal - Negative Appraisal (PASA) scale [11], administered before and after a stress episode.

Furthermore, perceived stress has been shown to correlate with fluctuations in self-assessed (negative) affect [9, 12]. Self-assessment provides a useful tool for characterising stress episodes, namely, by quantifying how the subjects experience it from an emotional point of view. This can also be measured pre- and post-stress using appropriate scales, such as the Positive and Negative Affect Schedule (PANAS), and serves as an alternative construct for stress characterisation [11].

Recently, the automatic detection of stress using various wearable sensors has seen increased popularity in the community, as timely detection of stress factors and corresponding reactions to them can facilitate the development of appropriate interventions to mitigate them. Among others, electrodermal activity, heart-rate, and speech have been effectively used to detect and quantify stress responses. As obtaining data from real-life stress episodes is obtrusive to the subjects’ privacy, thus raising ethical concerns, studies typically monitor subjects in a controlled environment where stress is induced – e.g., in the well-known Trier Social Stress Test (TSST) [13]. In our previous work, we investigated the feasibility of using speech obtained during a TSST to predict cortisol measurements obtained at specified intervals before and after the test [6]. Results from this study showed that audio-based features can be successfully used for that task, with recognition performance peaking for measurements obtained 10-20 minutes after the test (when individual cortisol measurements also peak).

However, predicting raw cortisol levels has limited usability in practical applications, where it is more important to measure the overall change to cortisol levels resulting from a stress episode. Moreover, a more holistic characterisation of stress responses is highly desirable. The main goal of this work is to investigate the feasibility of using audio features to model different facets of stress episodes: a physiological indicator (cortisol), the subject's cognitive appraisal, and the subject’s self-assessed affect. For example, changes in self-assessed (negative) affect levels measured using the PANAS scale prior to and following the TSST, as well as changes to the stress index (SI) constructed based on the PASA scale [11], provide alternative lenses with which to characterise stress episodes for each individual. Specifically, we investigate three questions: a) to what extent each of these indicators can be modelled in isolation, b) how complimentary is the information contained in each of them, and c) whether there are subject-specific effects at play that influence how stress manifests in the audio signal.
The remainder of this paper is organised as follows. In Section II, we describe the dataset, as well as the process we used to generate our targets. Section III introduces the methodological approaches we used for modelling. Section IV includes our results, and Section V offers some concluding remarks.

II. DATASET

Our work is based on the Regensburg Trier Social Stress Test (REG-TSST) dataset, first introduced in [6]. A total of 27 subjects (13 male, 14 female) aged [19-29] years old (median: 22) were recruited from the University of Regensburg campus and the surrounding community. The entire study, including the questionnaires, instructions, and TSST was conducted in German. The study was approved by the Ethics Committee of the University of Regensburg on November 11, 2014 (No. 14-101-0283).

Subjects received verbal and written instructions upon arrival, followed by a resting period. During this time, a first saliva sample (T1 – 30-45 minutes before the TSST) was collected and a sugary drink (chilled herbal tea with 75 g of glucose) was given to elevate blood glucose levels [14]. The participants were given the PANAS and PASA questionnaires to fill in. One minute before the next stage, another saliva sample was taken (T2 – 1 minute). The subjects were then guided to the test room and introduced to the observers, at which point the TSST commenced and the audio recording began.

Subjects were initially instructed to take the role of a job applicant and give a five-minute speech to present themselves as the best candidate for a vacant position. At the end of the interview stage, subjects were given a mental arithmetic task lasting for a further five minutes, where they should serially subtract 17 from 2043 as quickly as possible. After completion of both TSST tasks, six more saliva samples were taken from the subjects (T3-T8). The first was taken immediately after the end of the arithmetic task (T3 – +1minute) and the rest at the following intervals after that: +10, +20, +30, +45, +60 minutes. All saliva samples were analysed with a fluorescence-based immunoassay (DELFI A) to extract cortisol values measured in nanomoles per litre (nmol/l). Additionally, the subjects were once again given the PANAS and PASA questionnaires to gauge their cognitive appraisal in retrospect and affect self-assessment.

Audio was captured using two different devices, namely a far-field microphone placed above the interviewee and a close-talk one worn by them (AKG PW45 presenter set). For our experiments, we used the latter one as it resulted in cleaner recordings. All recordings were converted to 16 kHz, 16bit, mono, WAV format and applying peak normalisation to −1 dB for each audio file, i.e., adjusting the loudness based on the maximum amplitude of the signal.

Based on the measured cortisol values and PASA/PANAS questionnaires, we constructed three targets corresponding to changes in each of the three indicators considered.

- **Cortisol**: the first such target is the change in cortisol values with respect to the baseline caused by the TSST.
- **Appraisal**: the second target is the difference between SI values measured before and after the TSST using PASA.
- **Affect**: the final target is the difference in negative affect before and after the TSST measured with the PANAS scale, as only negative affect has shown a correlation with stress [12].

Histogram plots for the three targets are presented in Figure 1. Most subjects show an increase in cortisol values (range: [-0.67, 23.6] nmol/l, median: 4.25 nmol/l) showing that their cortisol levels increased as a result of the TSST. Changes to SI (range: [-3.5, 1.5], median: -0.38) and negative affect (range: [-0.5, 2.2], median: 0.55) were more balanced on average. For operationalisation purposes, all targets are scaled to a [0 – 1] range when modelling. This allows us to have a bounded target range, which makes training more stable, and additionally facilitates a coarse comparison between the results for each of the three targets.

III. EXPERIMENTAL SETUP

Previous work has shown that segmenting the entire recording using overlapping windows, extracting segment-level features from each window, and subsequently treating the resulting sequence as input to a recurrent architecture, can be effectively used for stress recognition in a TSST setting. We follow the same modelling paradigm here.

Specifically, we use the openSMILE toolkit [15] to extract the extended Geneva minimalistic acoustic feature set (eGeMAPS) [16] with a window of 1 s and a hop size of 0.5 s. This results in a total of 88 features for each window; with the feature set comprising frequency- (pitch, jitter, formant frequency), energy- (shimmer, loudness, harmonics-to-noise ratio), and spectral-related parameters (alpha ratio, Hammarberg index, spectral slope, formant energy, harmonic difference). As typically done in audio processing, those features are normalised to have 0 mean and a standard deviation of 1. The normalisation parameters are computed on the training set and applied to the entire dataset.

The sequence of feature vectors is then fed into a gated recurrent unit (GRU) network with 64 hidden units, which...
sequentially process its input feature sequences and produces an equal number of hidden representations. We used two variants: a vanilla one where the output of the GRU is first mean-pooled and then fed into a linear layer to obtain the final prediction, and one where mean-pooling is substituted with attentional pooling. In both cases, dropout with probability 0.2 is applied to the output of the pooling layer for regularisation purposes. All networks are trained for a maximum of 100 epochs on the training set using stochastic gradient descent (SGD) with a learning rate of 0.001 and a Nesterov momentum of 0.9. A batch size of 16 is used during training, with all sequences padded to a maximum length of 1,200 (10 minutes). The models are early-stopped based on validation set performance.

Attentional pooling corresponds to a (dot-product) self-attention mechanism acting on the output of the GRU. Given a sequence \( X \in \mathbb{R}^{d \times T} \), where \( d \) is the feature dimensionality and \( T \) the time dimension, dot-product self-attention uses a trainable weight matrix \( W \in \mathbb{R}^{d \times 1} \) to project that sequence into a time-sequence \( Z \in \mathbb{R}^{T \times 1} \). This time-sequence is converted into a sequence of (pseudo-)probabilities using the softmax operator \( (\alpha = \text{Softmax}(Z)) \) which serve as weights to the input sequence \( X \). After the weights \( \alpha \) are multiplied with \( X \), the resulting sequence is summed over the time dimension to produce the output feature vector \( F \in \mathbb{R}^{d} \). Concretely:

\[
Z = X \times W, \\
\alpha = \text{Softmax}(Z), \quad \text{and} \\
F = \sum_{1}^{T} (\alpha \cdot X).
\]

The attention matrix \( W \) then learns to assign importance to different points in the sequence \( X \); a fact we later exploit to find which parts of the TSST contribute more to the final decision.

Aside from the standard methodology described above, we investigate two additional facets of modelling the three herein considered stress indicators. The first is whether the information contained in each of them is complimentary to one another. An experimental investigation of that question can be provided by jointly modelling all three of them in a multi-task setup and measuring whether performance increases. This is implemented by changing the output of the network to have a dimensionality of 3. All other settings remain the same.

The second question pertains to the extent in which the manifestation of stress in voice depends on the individual; individual differences would in turn manifest in the features we are extracting. A typical way to mitigate such differences is to perform speaker-based feature normalisation: instead of computing global normalisation parameters based on the training data, and subsequently applying it to all instances, as is the standard process, the data from each speaker is normalised independently (including speakers in the dev/test set). If such a normalisation were to improve performance, it would serve as an indication that individual effects play an

| Model          | Normalisation | Cortisol | Appraisal | Affect |
|----------------|---------------|----------|-----------|--------|
| GRU-STL        | Standard      | .20/-    | .33/-     | .27/-  |
|                | Speaker       | .18/-    | .31/-     | .25/-  |
| GRU-MTL        | Standard      | .16/-    | .24/-     | .26/-  |
|                | Speaker       | .15/-    | .22/-     | .26/-  |
| AGRU-STL       | Standard      | .18/-    | .29/-     | .27/-  |
|                | Speaker       | .22/-    | .23/-     | .25/-  |
| AGRU-MTL       | Standard      | .16/-    | .27/-     | .24/26 |
|                | Speaker       | .14/19   | .21/26    | .28/-  |

TABLE I: Cortisol, appraisal, and affect MAE on the development and test set (dev/test). Targets were constructed as difference of values measured before and after the TSST, and their scale was normalised to \([0 - 1]\). Cortisol corresponds to raw cortisol values (measured in nmol/l), appraisal to Stress Indices (SIs) obtained via the PASA scale, and affect to negative affect assessed with PANAS. Test results only reported for the best-performing combination of each target to avoid overfitting (selection done on the dev set).

Mean absolute error (MAE) results for all experiments are presented in Table I. Following standard practice, we evaluate all configurations on the validation set, but only the best ones on the test set to avoid overfitting. Overall, the best results are obtained using attentional pooling and multitasking – in line with previous results showing that both mechanisms generally improve performance. This is true when considering the two factors in isolation as well: (A)GRU-MTL is better than (A)GRU-STL and AGRU better than GRU. Moreover, Table I shows that cortisol prediction yields consistently lower MAE results than the other two targets. While a comparison of (non-linear) regression results for different targets is not straightforward, this indicates that physiological responses to stress are more clearly manifested in the speech signal.

Interestingly, speaker-based normalisation yields the best performance for changes to cortisol and SI, indicating that the effect of stress on voice differs across individuals. Moreover, speaker-based normalisation is almost universally better than standard normalisation for all experiment configurations, lending further evidence to that claim. This shows that more advanced personalisation approaches would be beneficial.

Finally, we visualised attention weights for all test samples in Figure 2. We computed the mean (solid line) and standard deviation (shaded area) over all subjects of the attention
weights given by Equation (2). This shows the importance assigned by the network to each timestep. An interesting trend is revealed: the MTL network emphasises the first ∼ 500 samples of the TSST – a time span corresponding to the interview task. This trend is particularly pronounced when using speaker-based normalisation. In contrast, the STL network trained on the appraisal target shows a slight tendency towards the arithmetic task. This shows how stress may manifest differently in the two TSST tasks; future work could thus treat them separately.

V. CONCLUSION

We investigated the prediction of three stress-related constructs (changes to cortisol values, cognitive appraisal, and self-assessed affect) using speech features acquired during a TSST. Our analysis showed that the three constructs manifest differently in the speech signal, that there appear to be subject-specific effects in their manifestation, and that their information can be utilised in complimentary fashion. Predicting those targets using speech signals obtained in a TSST setting constitutes a first step towards the unobtrusive detection and characterisation of real-life stress episodes.

ACKNOWLEDGMENT

The work leading to this publication has received funding from the DFG’s Reinhart Koselleck project No. 442218748 (AUDI0NOMOUS). Data collection was supported by grant number DFG-KU 1401/6-1 assigned to B. M. K.

VI. REFERENCES

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