

Tactics to optimize the potential, a stress management training strategy, and experience modify independently phasic and tonic electrodermal activities of residents during critical simulated situations

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Introduction

ℜ Resuscitation situations can induce stress for the caregiver (Verma et al. 2015).

- Recognized Stressfull factors in these situations are :
 - A lack of controlability of the situation
 - Onpredictable situation
 - A long duration resuscitation

✗ During the situation: stress reaction decreases cognitive performances (Arnsten et al. 2009; Arnsten et al. 2012).

✗ Higher prevalence for stress-induced diseases for resuscitator comparatively to other category of caregivers (Douglas et al. 2005, Rabkin et al. 2009).



Introduction

High Fidelity Simulation



- For resuscitation: HFS has shown its efficacy for learning and for improving behavioral performances (Lilot et al. 2018).
- HFS is known to induce acute stress in the participant through immersive and realistic situations and can conduct to a decrease of cognitive performance (Bauer et al 2016; Nielsen 2013; Harvey et al 2012; LeBlanc 2009).



Introduction

X Tactics to Optimize Potential (TOP) :

- Initially developped in the french army.
- Aim to improve performance by preparing to the action, during action and promoting recovery after action.
- TOP practice has shown its ability to reduce perceived stress (Trousselard et al. 2015).
- => This tool could have a daily interest for the resuscitators



Objective

Could Tactics to Optimize Potential help :

- Resident in intensive care
 - Improving their performance during resuscitation situations ?

Improving stress management ?



 \gtrsim Inclusion of 128 residents in intensive care from the 1st to the 5th year.

Randomization in 2 groups :

Control

TOP : training during 5 hours to the TOP.



KHFS performed at the CLESS : (Centre Lyonnais d'Enseignement par la Simulation en Santé)

Stratification following intervention and year of experience Visual Analogic Scale "stress" Activation state







Service de santé

des armées



K Identifying tonic and phasic EDA



K Evaluation of clinical performance with a composite index by two assessors :

- Technical skills evaluation:
 - According to a preestablished scenario-specific checklist
- Non-technical skill evaluation:
 - According to the level to the Ottawa Crisis Resource Management Global Rating Scale
 - According to the level to the TEAM (Team Emergency Assessment Measure)



X Overall, Technical and Non-technical performances







Stress management TOP effects





Stress management TOP effects : phasic EDA

1,6



des armées



% Stress management

Experience effect : tonic EDA



Discussion

X TOP practice and experience act on two different components of the EDA.

✗ Experience could be a global process acting on the tonicity of the system

✗TOPs could act on the amygdala reactivity as observed with fMRI with cognitive therapy (Gingnell et al 2016).



Conclusion

X TOPs during simulation preparation period have beneficial effect on:

- Performances
- Psychology
- Physiology

X TOP has not same benefit than experience

Curve Section 2015 Contract Section 2015 Con



Thank you for your attention!



O— Les TOP

Boîte à outils comprenant un certain nombre de techniques. Chacun doit sélectionner, personnaliser et perfectionner sa boîte.





Manuel TOP, 2013 - CNSD

Matériels et Méthodes

Séparation EDA phasique et tonique

cvxEDA: a Convex Optimization Approach to Electrodermal Activity Processing

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Abstract-Goal: This paper reports on a novel algorithm for the analysis of electrodermal activity (EDA) using methods of convex optimization. EDA can be considered one of the most common observation channels of sympathetic nervous system activity, and manifests itself as a change in electrical properties of the skin, such as skin conductance (SC). Methods: The proposed model describes SC as the sum of three terms: the phasic component, the tonic component, and an additive white Gaussian noise term incorporating model prediction errors as well as measurement errors and artifacts. This model is physiologically inspired and fully explains EDA through a rigorous methodology based on Bayesian statistics, mathematical convex optimization and sparsity. Results: The algorithm was evaluated in three different experimental sessions to test its robustness to noise, its ability to separate and identify stimulus inputs, and its capability of properly describing the activity of the autonomic nervous system in response to strong affective stimulation. Significance: Results are very encouraging, showing good performance of the proposed method and suggesting promising future applicability, e.g., in the field of affective computing.

Index Terms—Convex optimization, electrodermal activity, skin conductance, sparse deconvolution.

I. INTRODUCTION

T LECTRODERMAL activity (EDA) broadly refers to any alteration in the electrical properties of the skin. One of the most frequently used measures of EDA is skin conductance (SC). Electrodermal signals are a manifestation of the activity in eccrine sweat glands that are innervated by the sympathetic branch of the autonomic nervous system (ANS), mainly by the sudomotor nerves [1]. Indeed, when the sudomotor nerves stimulate the production of sweat, the conductivity measured on the skin surface changes as a result of sweat secretion and of variations in ionic permeability of sweat gland membranes [2]-[4]. Although sweating is primarily a means of thermoregulation, sweat glands located on the palmar and plantar (glabrous) surfaces possibly evolved to increase grip and enhance sensitivity, and may be more responsive to psychologically significant stimuli than to thermal ones [2],

[4]. This relationship between EDA, ANS, and psychological stimuli — together with the relative ease of measurement makes this physiological signal widely popular in neuroscience research, including information processing, quantification of arousal levels during emotional and cognitive processes, and clinical research examining predictors and correlates of normal and pathological behaviour [5]–[7].

The SC signal can be decomposed in two components, tonic and phasic, which have different time scales and relationships to the triggering stimuli. Tonic phenomena include slow drifts of the baseline skin conductance level (SCL) and spontaneous fluctuations (SF) in SC [4]. The phasic component, skin conductance response (SCR), reflects the short-time response to the stimulus. The typical shape of the SCR comprises a relatively rapid rise from the conductance level followed by a slower, asymptotic exponential decay back to the baseline.

When the interstimulus interval (ISI), i.e. the temporal gap between two consecutive stimuli, is shorter than the recovery time of the first response, the two SCRs overlap. This occurrence is observed in many experimental paradigms, particularly in cognitive neuroscience where commended minimum ISI to avoid such an overlap, which is around 10– 20 s [5], [8]. The overlap issue is probably the main limitation in a set of factors regarding the decomposition of SC into its phasic and tonic components. Despite the wide use of EDA measurements, the generation of SCR via skin sympathetic nerve fibres remains an understudied topic.

In the past two decades, several mathematical solutions have been developed to decompose the phasic signal into individual SCRs associated to each stimulus, even during short ISI experimental paradigms, and to model how ANS activity (and, in particular, the sudomotor nerve activity) causes SCRs. This process allows estimation of ANS activity with potentially better time resolution than using the raw SCR signal. Many of the early methods, whose primary aim was to overcome the overlap issue, required visual inspection and introduced

