Physiological Responses to Error Amplification in a Robotic Reaching Adaptation Task

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Abstract— **Analysis of physiological responses provides an objective measure of a person's affective state and has been proposed as a way to evaluate motivation and engagement of therapy clients during robot-assisted therapy regimens. This paper presents the analysis of three physiological responses to different levels of error amplification in a robotic reaching task to understand the feasibility of using physiological signals in order to modify therapy exercises to achieve higher participant attentiveness. In a pilot study with 22 healthy participants, we analyzed skin conductance, skin temperature, and respiration signals, with two main goals: 1) to compare physiological parameters between baseline (rest) and error-amplified reaching motion periods; and 2) to compare physiological parameters between reaching motion periods with different levels of error amplification. Results show that features extracted from skin conductance and respiration signals show significant differences between different error amplification levels. Features extracted from the skin temperature signal are not as reliable as measures of skin conductance and respiration, however they can provide supplementary information.**

I. INTRODUCTION

Motor rehabilitation exercises are designed to stimulate neuroplasticity through a high dose of repetitive training. While conventional therapy focuses on reducing movement errors, recent findings in motor learning and artificial intelligence suggest that learning is indeed largely an error-driven process [1, 2]. Based on these findings, the field of robot-assisted therapy has been expanded to explore the effects of providing feedback to the user via augmentation of movement errors [3-5]. Error augmentation, a visual and/or force feedback that magnifies motion deviations of the user from a "healthy" trajectory, has been shown to improve the rate of motor learning in the stroke population [6] and makes repetitive exercise more challenging, which can lead to higher engagement during exercise [7].

Engagement and motivation of the therapy client is a key factor in the success of a therapy regimen as it directly correlates to how long the therapy client will continue with the exercises [8]. A possible way to ensure that the user will maintain a minimum level of engagement in therapy tasks is to design a closed-loop system capable of tuning the therapy exercises based on the user's affective state. The challenge then will be to quantify the state of the user without interrupting the course of exercise.

Physiological signals processing to gauge affect in human-robot interaction scenarios has gained popularity in recent years. Skin conductance response (SCR), skin temperature (TEMP), and respiration rate (RESP) are among the autonomic nervous system responses that are well correlated with cognitive and physical workload, emotional arousal, anxiety and attention [9-12]. SCR increases with emotional arousal and attentiveness, or during mentally demanding tasks. Skin temperature has a negative correlation with anxiety and cognitive workload. Respiration rate and respiration rate variation are also correlated with cognitive and physical load and emotional arousal.

In a former study [7], we showed that doing a reaching exercise with different levels of error amplification (i.e., low gain vs. high gain and visual vs. visual plus force feedback) leads to different levels of motor adaptation and affective states. Moreover, participants reported different levels of perceived difficulty for each error amplification (EA) level. Building on the findings of that study, we propose to use physiological signal analysis to evaluate the user's affective state during exercise in order to change and modify the difficulty of the reaching exercise (i.e., level of EA) in a closed-loop system. The first step toward such a closed-loop system would be to verify that practicing with different levels of EA will affect the user's physiological signals and will lead to different responses.

Error amplification levels used in [7] present different levels of cognitive workload (amplification gains) and different levels of physical workload (presence of force feedback). Our goal in the study presented in this paper is to understand whether varying the level of error amplification leads to different physiological responses. Using the same experiment protocol as in [7], we have examined three physiological responses: skin conductance, skin temperature, and respiration. The findings from this study will be used in identifying physiological features that are best correlated with cognitive and physical load associated with practicing the robot-assisted EA reaching motions.

In Section II of this paper we provide the details of our experimental and analytical methods. Section III provides a discussion of the results, and Section IV concludes by reflecting on the findings of this work.

II. METHODS

A. Hardware

A custom-built five-bar robotic manipulandum was used

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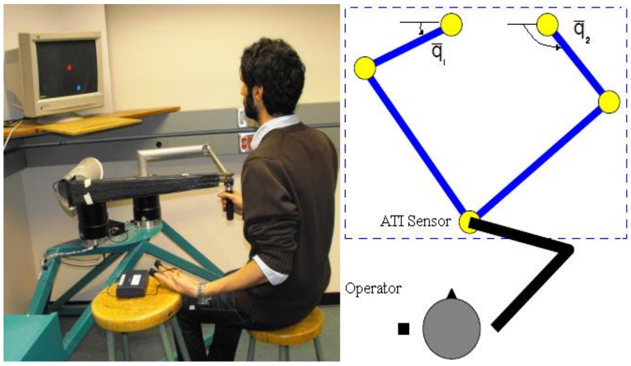


Fig. 1. Left: Participants interact with the robot by moving its end-effector in the horizontal plane [7]. SCR data are collected from the fingertips of the participant's left hand. Right: Schematic top view of the manipulandum.

in this study. The robot provides a horizontal reaching area of approximately 50 cm × 35 cm (Fig. 1). Two motors located at the base (robot's shoulders) actuate the robot. Position feedback is supplied through encoders that are integrated with the motors. Using TargetDisplay (MathWorks, Inc.), the position of the end-effector is visually rendered on a flat screen monitor as a moving dot, refreshed at 20 Hz.

A ProCompInfiniti Physiology Suite System (Thought Technology, Ltd.) was used to collect participants' physiological signals at 256 Hz. Temperature was measured using a sensor strapped around the distal phalange of the ring finger of each participant's dominant hand. SCR was recorded using two electrodes strapped around the distal phalanges of the index and middle fingers of the dominant hand. The breathing rate sensor was placed on a strap around the participant's chest. Temperature and SCR sensors were placed on the dominant hand and participants were asked to interact with the robot with their non-dominant hand.

B. *Reaching Task, Distortion, and Error Amplification*

Participants were instructed to reach for visual targets presented on the monitor by moving the cursor via manipulation of the robot handle. The flat screen monitor was mounted in front of the participant. To make sure that the only visual feedback was through the monitor, the reaching space was covered. Three targets were placed radially, 120° apart, at a constant radius from the middle of the screen (i.e., start position). When a target was highlighted, participants had to move the robot handle to place the moving dot over the target, and then move back to the start position.

To cause an initial error and a decrease in performance of the healthy participants, and thus to initiate motor adaptation, visual distortion was implemented (blind to participants). To implement visual distortion, actual hand movement (handle position) was rotated 30°, and then the rotated position was presented as the moving dot on the monitor. Each subject would then train in 5 exercise blocks, receiving a different level of EA in each block, to adapt to reaching within the rotated environment. Five levels of error amplification are: reaching without EA (control), reaching with low-gain visual EA, reaching with high-gain visual EA, reaching with low-gain visual and force feedback EA, and reaching with high-gain visual and force feedback EA. These were implemented as described in [7]. Visual EA was implemented with a low gain of 1.30 and a higher gain of 1.65. Force feedback EA gains were designed to map the trajectory errors to force ranges of 0-5 N at the lower gain and 0-8 N at the higher gain.

C. *Participants and Study Protocol*

Twenty-two healthy participants with normal or corrected vision took part in this study. As approved by the Clinical Ethics Research Board of the University of British Columbia all participants were required to provide written informed consent. The male female ratio of the participants was 10/12 and the average age was 24.3.

The data collection protocol was similar to that of [7]. We collected the data in six exercise blocks. In the first block (familiarization), participants performed 14 cycles of plain motions (reaching motions without rotational distortion or EA). A cycle consists of one reaching motion to each of the three targets in random order. This familiarization block was followed by five training blocks.

Within each of the training blocks, participants practiced 10 cycles of plain motion (de-adaptation), and 13 cycles of reaching at one of the EA levels "within" the rotated environment (EA cycles). The de-adaptation cycles are aimed to wash out the learning effects of the previous training block. The order of the EA levels was defined using a random number generator. There was a one-minute rest period between de-adaptation and EA cycles. Physiological data were collected during both the rest period and the EA cycles.

III. RESULTS

In the first phase of the data analysis, we compared the differences in the physiological measures between rest (baseline) and training periods. This was done for each EA level as a t-test with period type (baseline vs. training) as the within-subject factor. This was aimed at understanding whether or not the reaching exercise causes significant physiological changes from baseline values.

In the second phase of the data analysis, we compared the differences in the normalized physiological measures between levels of EA (differences between different training periods). This was done for each physiological measure as an ANOVA test with the training type (levels of EA) as the within-subject factor. This was aimed at understanding whether or not levels of EA produce significant physiological changes compared to each other.

A. *Physiological Measures*

In the first phase of the data analysis, we compared seven physiological measures between rest and training periods: **mean SCR** as period average of SCR, **peak SCR** as period maximum of SCR, **mean dSCR** as period average of SCR rate of change, **mean RESP** as period average of respiration rate, **RESP variability** as period standard deviation of respiration rate, **mean TEMP** as period average of skin temperature, and **TEMP variability** as period standard deviation of skin temperature.

In the second phase of the data analysis, we compared ten physiological measures between training periods (i.e., levels of EA): **norm mean SCR** defined as mean SCR in the training period divided by mean SCR in the rest period, **SCR peak value** defined as the difference between minimum SCR and maximum SCR during training period, **SCR change** defined as the difference between the mean SCR in a consecutive rest period and training period, **norm dSCR** defined as mean dSCR in the training period divided by mean dSCR in the rest period, **norm RESP** defined as mean RESP in the training period divided by mean RESP in the rest period, **RESP change** defined as the difference between the mean RESP during the training period and mean RESP during the rest period, and **RESP variability** defined as the standard deviation of respiration rate in the training period, **norm TEMP** defined as mean TEMP in the training period divided by mean TEMP in the rest period, **TEMP change** defined as the difference between mean TEMP during the training period and mean TEMP during the rest period, and **TEMP variability**, defined as the standard deviation of TEMP in training period.

B. Baseline vs Training Comparison

Table I shows results of the t-tests of the first stage of the data analysis to evaluate the differences between baseline and training periods. In general, significant effects were observed between the baseline and training periods, indicating that the cognitive and physical load of the training task is reflected in the physiological measures.

C. Comparison between Different Levels of EA

Fig. 2 shows the results of within-subject ANOVA tests of the second stage of the data analysis to evaluate the differences in physiological measures between training periods with different EAs (effect of each EA level on the physiological responses). In general, significant differences were observed between the training periods for all the measures shown in Fig. 2. Two of the physiological measures, *norm TEMP* and *norm RESP*, did not show any significant differences between the training periods and are not presented in Fig. 2.

TABLE I. DIFFERENCES OF BASELINE AND TRAINING PERIODS

	EA 1	EA 2	EA 3	EA 4	EA 5
mean SCR	*t*	*N/A*	*	*	**
peak SCR	*	*	*	*t*	*
mean dSCR	*N/A*	**	*	**	***
mean RESP	*t*	*	*	*	*t*
RESP variability	*	*	*	*t*	*
mean TEMP	*t*	*	*	*	*t*
TEMP variability	**	**	**	*	*

Significance of the differences between the baseline and training periods (for each error amplification level) are indicated with the following symbols: N/A $p > 0.10$, *t* $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

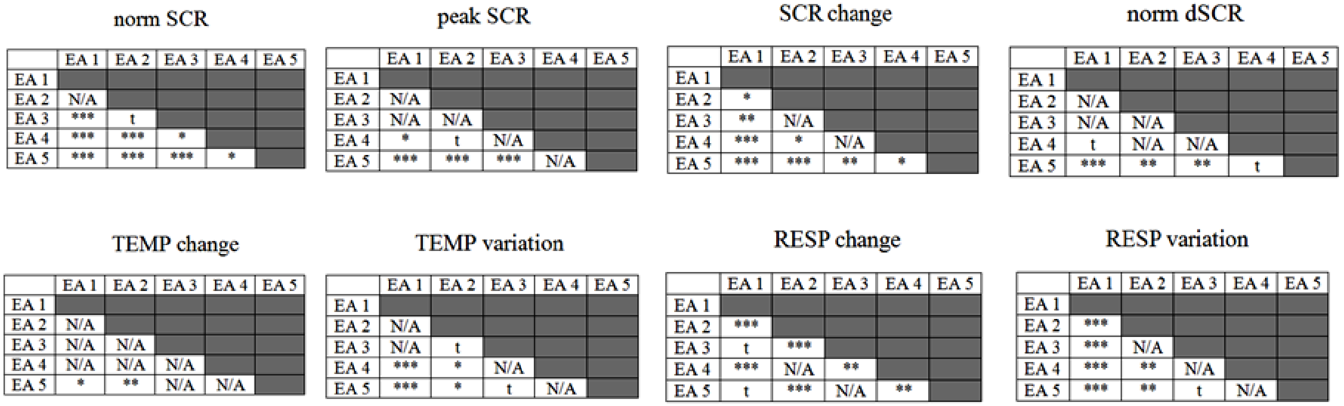
Five levels of error amplification are: EA 1) reaching without EA (control); EA 2) reaching with low-gain visual EA; EA 3) reaching with high gain visual EA; EA 4) reaching with low gain visual and force feedback EA; and EA 5) reaching with high-gain visual and force feedback EA.

IV. DISCUSSION AND CONCLUSION

As a step toward the design of closed-loop rehabilitation exercises capable of autonomously modifying the task based on the user's affective state, this paper is focused on effects of practicing reaching tasks with EAs on the user's physiological signals. First we examined whether a training period, regardless of the EA level, changes the physiological responses of the participants (Table I). Considering only the differences between baseline and training periods, skin temperature yields the most significant changes between the two periods (*Temp variability)*. Respiration signal shows significant differences between the two periods, however for a few of the EA levels we observed only a trend and the differences are not significant. Skin conductance seems to show less difference between the baseline and training. As highlighted by these results, it is not sufficient to consider only one physiological signal in affective computing, and a number of physiological features need to be considered simultaneously.

In the second phase of the data analysis, we focused on whether training with different levels of error amplification leads to different physiological responses. Also, we were interested in knowing which extracted measures from the physiological responses show the differences between training with different EA levels more strongly than others. In general, all three physiological signals we measured show differences between different training levels. This demonstrates that there are differences between cognitive and physical loads associated with a reaching exercise with different levels of error amplification. However, the differences observed in the skin conductance and respiration measures are more significant in comparison with those observed in the measures extracted from the skin temperature signal.

Participants ranked the perceived challenge of the error amplification levels, from hardest to easiest, as: high gain visual and force feedback EA, low gain visual and force feedback EA, high gain visual EA, low gain visual EA, Control EA (no error amplification) [7]. *RESP change* was the only measure that showed significant differences between all consecutive levels of EA challenges (Fig. 2: see significance values on the diagonal of the *RESP change* plot). The most reliable measures are *norm mean SCR* and *SCR change* since they demonstrate the most number of significant differences between different training periods. Changes in skin conductance are known to be a rapid way to identify emotional arousal. The fact that SCR measures show the most significant changes between the training levels indicates that participants practiced the reaching exercise with different levels of attentiveness depending on which EA they were receiving. *TEMP change,* on the other end of the



norm SCR

	EA 1	EA 2	EA 3	EA 4	EA 5
EA 1					
EA 2	N/A				
EA 3	***	t			
EA 4	***	***	*		
EA 5	***	***	***	*	

peak SCR

	EA 1	EA 2	EA 3	EA 4	EA 5
EA 1					
EA 2	N/A				
EA 3	N/A	N/A			
EA 4	*	t	N/A		
EA 5	***	***	***	N/A	

SCR change

	EA 1	EA 2	EA 3	EA 4	EA 5
EA 1					
EA 2	*				
EA 3	**	N/A			
EA 4	***	*	N/A		
EA 5	***	***	**	*	

norm dSCR

	EA 1	EA 2	EA 3	EA 4	EA 5
EA 1					
EA 2	N/A				
EA 3	N/A	N/A			
EA 4	t	N/A	N/A		
EA 5	***	**	**	t	

TEMP change

	EA 1	EA 2	EA 3	EA 4	EA 5
EA 1					
EA 2	N/A				
EA 3	N/A	N/A			
EA 4	N/A	N/A	N/A		
EA 5	*	**	N/A	N/A	

TEMP variation

	EA 1	EA 2	EA 3	EA 4	EA 5
EA 1					
EA 2	N/A				
EA 3	N/A	t			
EA 4	***	*	N/A		
EA 5	***	*	t	N/A	

RESP change

	EA 1	EA 2	EA 3	EA 4	EA 5
EA 1					
EA 2	***				
EA 3	t	***			
EA 4	***	N/A	**		
EA 5	t	***	N/A	**	

RESP variation

	EA 1	EA 2	EA 3	EA 4	EA 5
EA 1					
EA 2	***				
EA 3	***	N/A			
EA 4	***	**	N/A		
EA 5	***	**	t	N/A	

Fig. 2. Pairwise comparisons of the differences in physiological measures between error amplification levels. Five levels of error amplification are: EA 1) reaching without EA (control); EA 2) reaching with low-gain visual EA; EA 3) reaching with high gain visual EA; EA 4) reaching with low gain visual and force feedback EA; and EA 5) reaching with high-gain visual and force feedback EA. Significance of the differences between training periods (error amplification levels) are indicated with the following symbols: N/A $p > 0.10$, t $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

spectrum, shows the least number of significant differences between the training periods. In contrast to their versatility in comparing between baseline and training periods, temperature measures show the least changes in comparison of the EA levels. This suggests that changes in temperature between baseline and training are only due to the reaching motions, and different levels of EA do not cause any further change in the skin temperature.

Due to the large differences between baseline values for each subject, relative values between baseline and training periods were used in comparing the effects of training EA levels on physiological responses. We explored two ways of computing relative values: subtracting the baseline value from the training value (i.e., *SCR change, RESP change, TEMP change*), and normalizing the training values by dividing them by the baseline values (*norm mean SCR, norm RESP, norm TEMP*). Although both *SCR change* and *norm mean SCR* show reliable performances, the normalization method does not yield reliable measures of skin temperature and respiration.

Of the three physiological responses examined in this study, skin conductance and respiration rate appear to be the most useful and robust. Features extracted from skin temperature signal are not as reliable as measures of skin conductance and respiration; however, they can provide supplementary information. Future studies will include correlating the physiological measures with self-reports of affective states. These correlations then will be used in designing a controller that maximizes the learning potential and attentiveness of a therapy client during the course of training via manipulating the level of error amplification.

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