An Approach to Validate an Agent Model for Human Work Pressure

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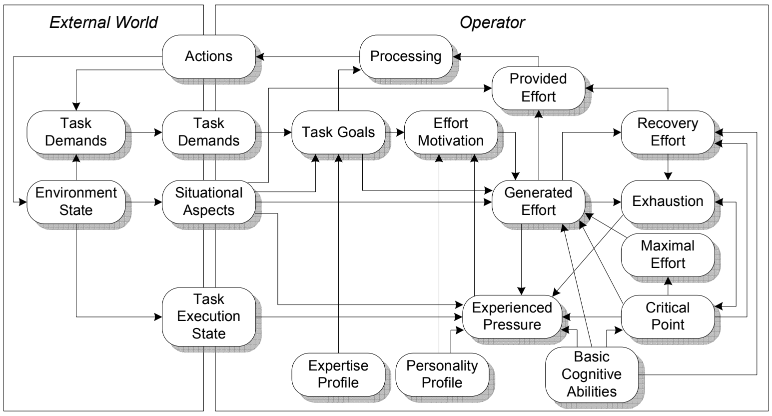
Background and Contribution

- In demanding working circumstances the quality of the tasks performed by a human might degrade.
- To improve task performance, personal assistant agents may be used.
- An agent is able to reason about states of the human and to give the most appropriate and effective support, when required.
- To enable this, the human work pressure model developed previously (Bosse et al., 2008) can be applied.
- To ensure that human states are recognized correctly and a proper support is provided to the human by the agent, the human work pressure model should be valid.
- In this work an approach is proposed to validate the existing work pressure model.
- In the validation approach parameter estimation is crucial step.

Agent model for an Operator's Functional State (1)



Agent model for an Operator's Functional State (2)

$$\partial Exhaustion(t)/\partial t = Pos(\eta \cdot (GeneratedEffort(t) - CriticalPoint(t))) - \pi \cdot RecoveryEffort(t)$$

$$\partial GeneratedEffort(t)/\partial t = \beta \cdot (CurrentContributionEffort(t) - GeneratedEffort(t))$$

$$\partial ExperiencedPressure(t)/\partial t = \mu 1 \cdot Pos(ExperiencedPressureChange(t) \cdot (1 - ExperiencedPressure(t)) - \mu 2 \cdot Neg(ExperiencedPressureChange(t) \cdot ExperiencedPressure(t)$$

$$CurrentContributionEffort(t) = NoiseEffort(t) + \varepsilon \cdot \frac{MaximalEffort(t)}{TopMaximalEffort} \cdot EffortMotivation(t) \cdot (w1 \cdot (CriticalPoint(t) - NoiseEffort(t)) + w2 \cdot TaskLevel(t) + w3 \cdot MaximalEffort(t))$$

$$TopMaximalEffort = LowestCriticalPoint + \zeta \cdot (BasicCognitiveAbilities - LowestCriticalPoint)$$

$$EffortMotivation(t) = ExperiencedPressureInfluence(t) \cdot \left(\frac{1+\frac{1}{\gamma}}{1+\gamma \cdot e^{-\phi \cdot TaskLevel(t)}} - \frac{1}{\gamma}\right) \cdot \frac{1}{Expectation(t)}$$

*ExperiencedPressureInfluence(t) = 1 - (HighPressureSensitivity * Pos(ExperiencedPressure(t) - OptimalExperiencedPressure) + LowPressureSensitivity * Pos(OptimalExperiencedPressure - ExperiencedPressure(t)))*

ProvidedEffort(t) = GeneratedEffort(t) - RecoveryEffort(t) - NoiseEffort(t)

*RecoveryEffort(t) = Pos(α * (CriticalPoint(t) - GeneratedEffort(t))) * GeneratedEffort(t)* (BasicCognitiveAbilities - CriticalPoint(t)) / BasicCognitiveAbilities*

*CriticalPoint(t) = LowestCriticalPoint + (1 - Exhaustion(t)) * (BasicCognitiveAbilities - LowestCriticalPoint)*

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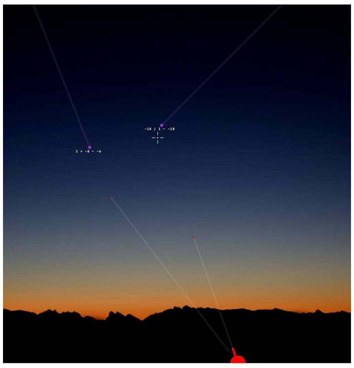
Experiments



- 31 subjects
- Experiment duration is approx. 1h
- 2-factor within subject design:
  Condition 1 (15 minutes):
  low task level – high task level
  Condition 2 (15 minutes):
  high task level – low task level
- Personal characteristics of the subjects were evaluated using NEO-PI-R and NEO-FFI questionnaires and short tests

Data

- Data from the experiment were used to calculate the values of several concepts from the work pressure model.

The personality profile

PerformanceNorm = B*Ambition+(1-5*B)

PerformanceSensitivity = C*Neuroticism + (0.5-5*C)

OptimalExperiencedPressure = 0.1*Extraversion*D- 0.1*Vulnerability*(1-D) + (1-D)

LowPressureSensitivity = 0, when OEP <= 0.33, LPS = 1, when OEP >0.33

HighPressureSensitivity = 1 when OEP < 0.67, HPS = 0 when OEP > 0.67

Basic Cognitive Abilities

Calc = % correct*minCalcRT/CalcRT

BCA = (W3*Calc + W4*Choice)*Z

Choice = minChoiceRT/ChoiceRT

The expertise profile and task level

Mouse-RT = %dist_to_centre *minMouse-RT/Mouse-RT

Exp = W1*Calc + W2*Mouse-RT

TaskLevel = (1.5 - Exp)*SitD

Performance quality

Effectivity = (1+ explosion_fraction)/2.0

ObjTES = (0.25*efficiency + 0.75*effectiveness)*2

Gradient-based parameter estimation

The method is based on the maximum likelihood principle

$$\hat{\theta}_{ML}{}^{k+1} = \hat{\theta}_{ML}{}^{k} + [\nabla_{\theta}{}^{2} E(\theta)]^{-1} \cdot [\nabla_{\theta} E(\theta)]$$

$$\hat{R} = \frac{1}{N} \cdot \sum_{i=1}^{N} (z_i - \hat{y}_i) \cdot (z_i - \hat{y}_i)^T$$

$$\nabla_{\theta} E(\theta) = \sum_{i=1}^{N} \left[\frac{\partial y_i}{\partial \theta} \right]^T \cdot R^{-1} \cdot (z_i - y_i)$$

$$\nabla_{\theta}{}^{2} E(\theta) = \sum_{i=1}^{N} \left[\frac{\partial y_i}{\partial \theta} \right]^T \cdot R^{-1} \cdot \left[\frac{\partial y_i}{\partial \theta} \right]$$

$$err = \sqrt{\sum_{i=1}^{N} \frac{(z_i - \hat{y}_i)^2}{N}}$$

Algorithm: ML-PARAMETER-ESTIMATION

Input: Initial values of the parameters θ^1, maximal number of iterations itmax; satisfactory error value err_sat; matrix of the input values U; matrix of the output values Z

Output: Maximum likelihood estimate θ_{ML}

1 i=1
2 Until $i \le itmax$ perform steps 3-7
3 Calculate the current state of the system using the model equations
4 Calculate the output root mean square error err^i.
5 if $err \le err\_sat$, then $\theta_{ML} = \theta^i$**; exit** endif.
6 if $i < itmax$, then
  6a Calculate the noise covariance matrix R
  6b Calculate the sensitivity coefficients $\partial y / \partial \theta$
  6c Calculate the first and second gradients.
  6d Calculate the parameter values for the next iteration θ^{i+1}
  endif
7 i = i+1
8 Find the minimum error err^m in $\{err^i | i=1..itmax\}$; then
  $\theta_{ML} = \theta^m$; **exit**

Simulated annealing

Temperature = computational-budget-left · error **(1)**

γ=γ+Temperature · (1-γ) · random_no_between[0,1] **(2a)**

γ = γ-Temperature · γ · random_no_between[0,1] **(2b)**

$$err = \sqrt{\sum_{i=1}^{N} \frac{(z_i - \hat{y}_i)^2}{N}}$$

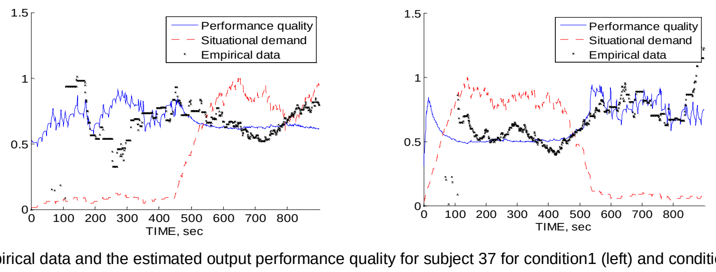
Algorithm:SA-PARAMETER-ESTIMATION

Input: Initial randomly selected values of the parameters , computational budget C; observed human behaviour B

Output: Best estimate of parameter settings θ_{BE}

1 $\theta_{BE} = \theta^1$.
2 while C ≥ 0 perform steps 3-8
3 Chose a random parameter setting θ in neighbourhood of θ_{BE} using equations 1, 2a and 2b.
4 Calculate the output root mean square error err for θ.
5 Calculate the output root mean square error err_{BE} for θ_{BE}.
6 if err ≤ err_{BE}, then $\theta_{BE} = \theta$**;** err_{BE} = err; endif.
7 Decrease C.
8 Temperature = C * err_{BE}.
9 **output** θ_{BE}.

Results of the parameter estimation (1)



Empirical data and the estimated output performance quality for subject 37 for condition1 (left) and condition 2 (right)

Error range		< 0.1	[0.1, 0.25)	[0.25, 0.4)	> 0.4
Subjects in condition 1	GB	21	11-20, 22, 24-41	-	-
	SA		40	11, 12, 22, 24-26, 30, 32-39, 41	13-18, 20, 21, 28, 29, 31
Subjects in condition 2	GB	12, 15, 18, 20, 21, 23, 27, 30	11, 13, 14, 16, 17, 19, 22, 24-26, 28, 32-41	29, 31	-
	SA	32	17, 26, 30, 31, 34. 35, 37, 40	12, 27, 38, 41	11, 13-16, 18-23, 25, 28, 29, 33, 36, 39

Results of the parameter estimation (2)

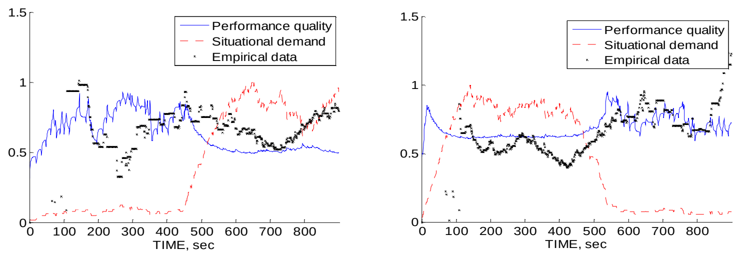
- To evaluate the quality of estimation also the Cramer-Rao measure was used

$$\sigma_\theta \geq \sqrt{I^{-1}(\theta)} \qquad (I(\theta))_{ij} = E\left[\frac{\partial^2 \log p(z \mid \theta)}{\partial\theta_i \partial\theta_j}\right]$$

- Using this measure at least 57% (70% in the best case) of the estimated parameters have been identified as accurate for all subjects in both conditions (relative standard deviation (rsd) $\leq$ 5%). Other parameters, although less accurate (5% < rsd < 40%) still have a degree of confidence.

- Using another measure - the correlation coefficients among the estimates - only one significant correlation between the parameters A and ϕ has been identified

Cross-validation



Predicted dynamics of the model for subject 37 in the condition 1 using the estimated parameters from condition 2 (left) and in the condition 2 using the estimated parameters from condition 1 (right).

Error range	< 0.1	[0.1, 0.25)	[0.25, 0.4)	> 0.4
GB	21	12-20, 22, 24-30, 34-40	11, 31, 32, 41	33
SA	-	17, 26, 31, 32, 37, 40	12, 13, 22, 25, 28, 30, 34, 35, 38, 41	11, 14-16, 18-21, 29, 33, 39

Conclusions & Discussion

- A number of parameters (35% in average) were evaluated as less accurate, and, therefore, less reliable.
- One reason for that is a large overall number of parameters being estimated.
- Another reason is that since the empirical data were collected based on irregular events, some temporal intervals contained the amount of information insufficient for estimation.
- Despite this, the models with estimated parameters demonstrated good predictive capabilities in the cross-validation, which is a strong indicator of the model validity.