An assistive handwashing system with emotional intelligence

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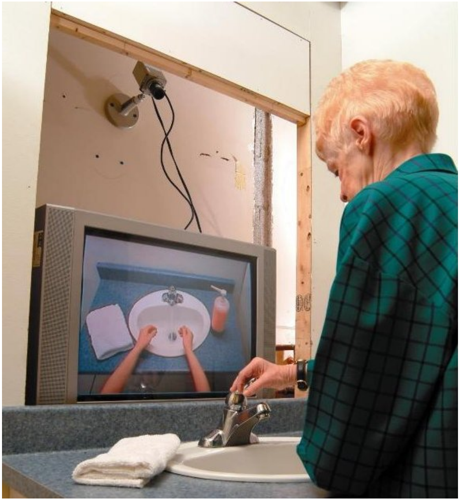
Agenda

Problem Statement - Motivation

The COACH system



- An assistive system helping people with dementia (e.g. Alzheimer's Disease) completing daily activities
- Works well for some persons, but not as well for others
- Only considers functional states of users

Problem Statement - Objectives

- Using Emotional Intelligence in Assitive Systems
- To augment the COACH system with an emotional reasoning engine so that the augmented system:
  - is designed in a portable and extensible way
  - runs in real-time from the perspective of the user group
  - provides a level of functional assistance
  - produces the prompts according to the emotional state of a user

Concepts - ACT

Affect Control Theory (ACT)

- represents emotions as EPA vectors, where E stands for "evaluation", P stands for "potency", and A stands for "activity"
- describes social events by an Actor-Behaviour-Object grammar
- "fundamentals" of identities and behaviours; shared between people within a same culture
- "transient impressions": emotional feelings caused by a specific event

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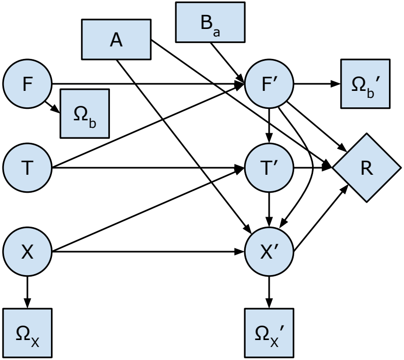
The ACT Principle

Actors work to experience transient impressions that are consistent with their fundamental sentiments.

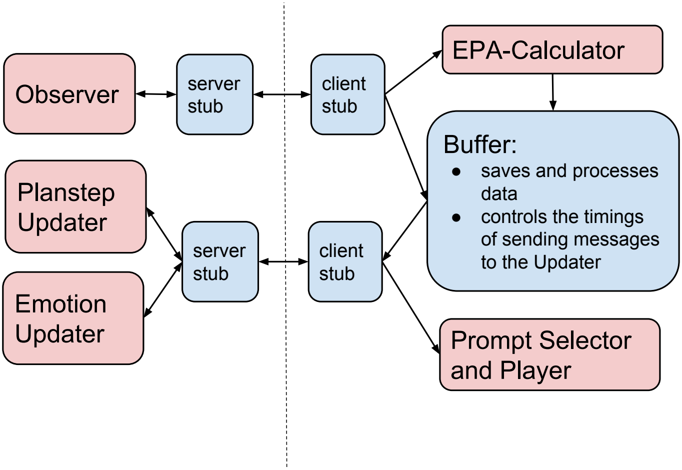
Concepts - BayesACT

- A Bayesian version of the ACT theory
- Extends the ACT with POMDP model
- Uses a "turn-taking" model and represents state variables for Agent, Behaviour and Client (ABC)

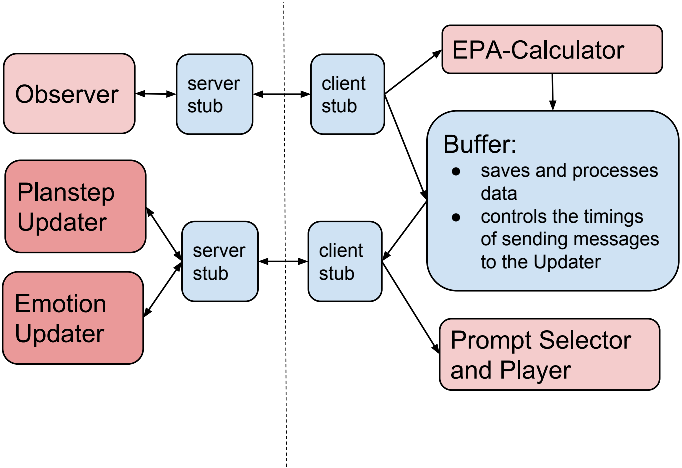


- States $S = \{X, F, T\}$, where $F = \{F_{ij}\}, T = \{T_{ij}\}, i \in \{a, b, c\}, j \in \{e, p, a\}$
- Note: F_c denotes the agent's belief of the client's identity
- Observations $\Omega = \{\Omega_X, \Omega_b\}$
- Actions $\{A, B_a\}$
- Calculate $\{A, B_a\}$ based on $\{X, F, T\}$

Design - Overview



Design - the Planstep and Emotion Updater



Design - the Planstep and Emotion Updater cont.

Use the BayesACT framework in the handwashing scenario

- Recall: BayesACT includes states $S = \{X, F, T\}$, observations $\Omega = \{\Omega_x, \Omega_b\}$, and agent actions $\{A, B_a\}$

Design - the Planstep and Emotion Updater cont.

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- Note: the "confidence" of Ω_b can be specified by γ, which is the variance of a normal (Gaussian) distribution.

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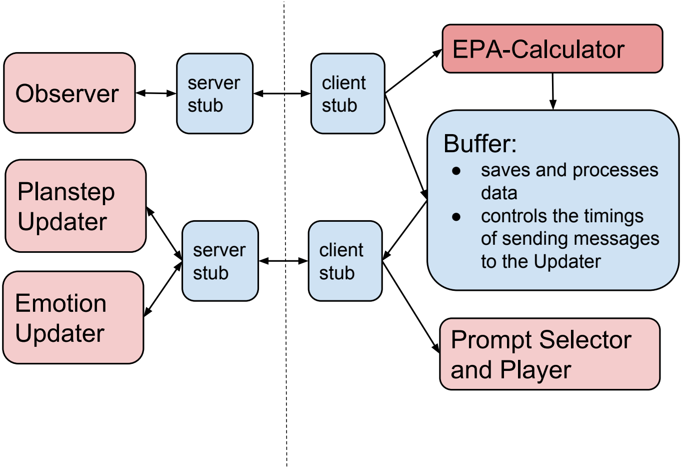
Design - the EPA-Calculator



Design - the EPA-Calculator cont.

- Calculates affective meanings of user behaviours
- Feature Selection
  - analysis on facial expressions and speeches?
  - related research for this special application scenario hasn't been done yet

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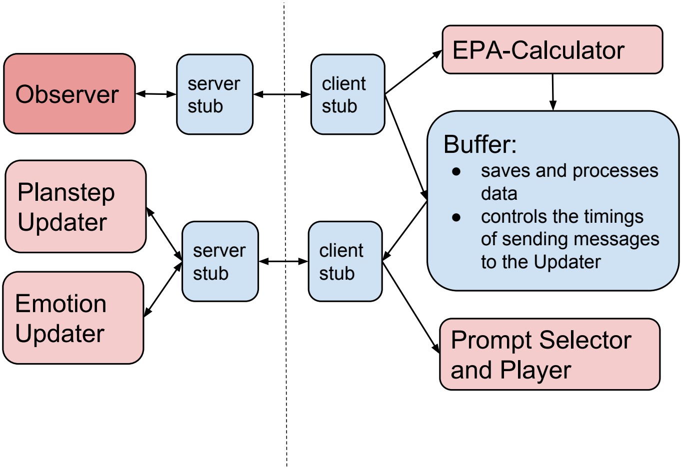
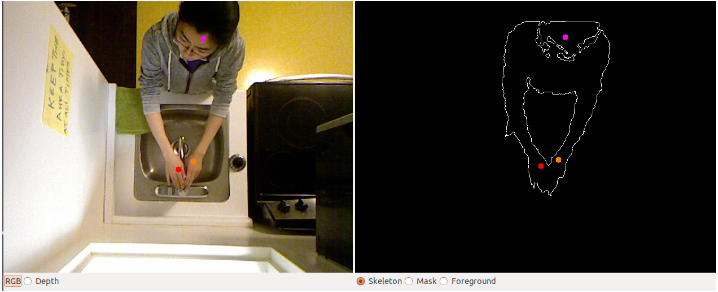
- Calculates affective meanings of user behaviours
- Feature Selection
  - analysis on facial expressions and speeches?
  - related research for this special application scenario hasn't been done yet
- Our approach
  - E stays neutral (value $= 0$); its value is ignored in the reasoning engine
  - P scaled from the expansiveness of the user's two hands
  - A scaled from the moving speeds of the user's hands
  - Used piecewise linear interpolation method
- "Confidence" of Ω_b can be specified in the reasoning engine

Design - the Observer



Design - the Observer cont.

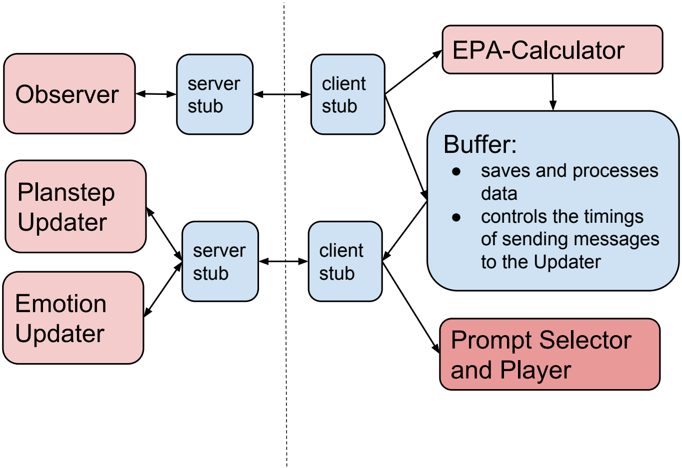
- Step 1: Get the locations of the user's hands
  - bases on a body tracker implemented in a previous work
  - obtains locations of body parts from depth images taken from an overhead perspective
  - was trained using partially labeled, unbalanced data, and is configurable and re-trainable



Design - the Observer cont.

- Step 2: Map locations to user behaviours
  - if hands are close to an object, then there's high probability of performing the behaviour corresponded to the object
- Observation noise handled by the observation function in the reasoning engine

Design - the Prompt Selector and Player



Design - the Prompt Selector and Player cont.

- The prompt dataset
  - 30 audio-visual prompts generated in a previous study
  - created using the USC Virtual Human Toolkit
  - EPA values of videos evaluated by human raters

- A proper prompt is selected as the final prompt if it:
  - has the same propositional labels as the desired prompt
  - has the closest emotional (EPA) values as the desired prompt

Experiments - Latency of the system

Average latency of the system

- 46.80ms for obtaining user behaviours
- 1.65s for calculating and updating functional and emotional beliefs
- 1.70s in total

The system runs in real-time from the perspective of its user group.

Experiments - Two laboratory tests

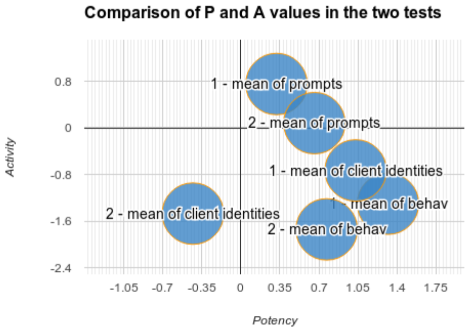
Two laboratory tests

- washed hands while the system observed and assisted in real time
- acted more powerfully and more actively in the first test than in the second
- results shown in thesis

15 further tests were also run. Results are in the Appendix.

Experiments - Conclusion

- Functionality performance
  - In general, the system is able to produce propositionally useful system prompts.
- Emotionality performance



Generally, user behaviours with higher P and higher A values lead to

- client identities with higher P and higher A values
- system prompts with lower P and higher A values

This is the same as predicted by the Affect Control Theory.

Discussion

Contribution

- designed, implemented and tested a prototypical hand-washing system that fullfills the objectives
- indicated a correlation between the EPA values of user behaviours, user identities, and system prompts

Future Work

- improve the EPA-Calculator
- improve the reasoning engine
- generate better prompt datasets
- conduct clinical trials for the system

Acknowledgement

This work is based on previous works of:

- Hoey, J., Schroder, T., & Alhothali, A. (2013, September). Bayesian affect control theory. In Affective Computing and Intelligent Interaction (ACII), 2013 Humaine Association Conference on (pp. 166-172). IEEE.
- Czarnuch, S., & Mihailidis, A. (2014 (in review)). Depth image hand tracking from an overhead perspective using partially labeled, unbalanced data: Development and real-world testing. IEEE Journal of Biomedical and Health Informatics.
- Malhotra, A., Yu, C., Schroder, T., & Hoey, J. (2014 (in review)). An exploratory study into the use of an emotionally aware cognitive assistant.

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- Families and friends, especially Chengbo Li, Xiao Yang, Enxun Wei and Luyi Lin

Thank you!

- Questions?
- Comments?

Concepts - BayesACT cont.

Model formulation

- The deflection $\phi(F, T)$ between F and T:

$$\phi(f, t) \propto e^{-(f'-t')\Sigma^{-1}(f-t)} \tag{1}$$

- The probability of a post-action fundamental sentiment f':

$$Pr(f'|f, t, x, b_a, \phi) \propto e^{-\phi(f',t')-\xi(f',f,b_a,x)} \tag{2}$$

  where t' can be computed from $\{f', t, x\}$ by empirically derived prediction equations of ACT.

- $Pr(x'|x, f', t', a)$: how the application progresses
- $Pr(\omega_b|f)$ and $Pr(\omega_x|x)$: observation functions for the client behaviour sentiment and system state

Update X'_{ps} based on Ω_x and $\{X_{ps}, X_{behav}, X_{aw}, F, T\}$

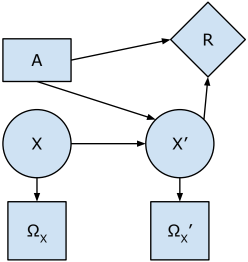
- $SampleXVar()$ and $evalSampleXVar()$
- Pseudocode of $SampleXVar()$ (on next page)
- $Pr : X_{behav} \to \Delta(\Omega_x)$ used in $evalSampleXVar()$

Update X'_{ps} based on Ω_x and $\{X_{ps}, X_{behav}, X_{aw}, F, T\}$ cont.

```
if Deflection(F, T) is high then
    threshold = high
else
    threshold = low
end if
if aw high then
    if prompted then
        if random_prob() < threshold then
            aw = low and not moving forward
        else if prompt wrong then
            aw = low and not moving forward
        else if likely then
            moving forward
        else if random_prob() < threshold then
            aw = low and not moving forward
        end if
    else
        if random_prob() < threshold then
            aw = low and not moving forward
        else
            aw stays high and moving forward
        end if
    end if
else
    if prompted then
        if random_prob() > threshold and prompt correct then
            move on and aw high
        else
            unlikely: aw high and not moving forward
        end if
    else
        unlikely: aw high and moving forward
    end if
end if
```

Concepts - POMDP

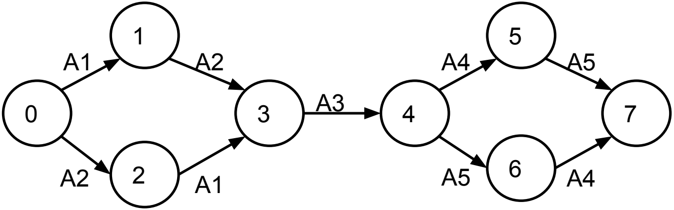
Partially Observable Markov Decision Process (POMDP)



- A timeslice of a POMDP process
- Variables: { X, A, $\mathbf{\Omega_X}$ }
- $Pr : X \rightarrow \Delta(\mathbf{\Omega_X})$,
  $Pr : X \times A \rightarrow \Delta(\mathbf{X})$
- Reward Function: $R(A, X')$

Solution - Representing "Functional States"

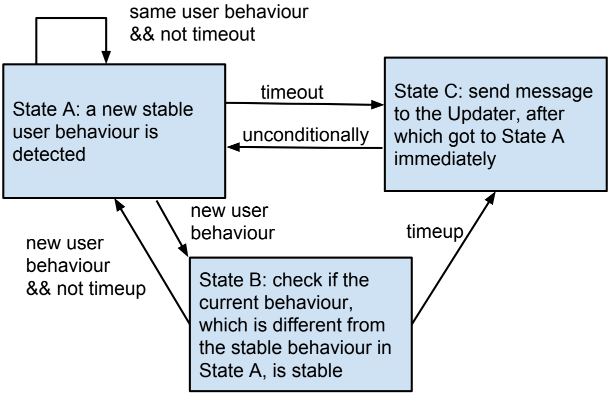
Planstep Definition and Update Diagram



- Eight plansteps: (0) "off/dirty/dry", (1) "on/dirty/dry", (2) "off/soapy/dry", (3) "on/soapy/dry", (4) "on/clean/wet", (5) "off/clean/wet", (6) "on/clean/dry", (7) "off/clean/dry"
- Five behaviours: A1 to A5 are "turn on water", "put on soap", "rinse hands", "turn off water", and "use towel", respectively.

Solution - The Buffer

- Between the Observer, the EPA-Calc, and the Reasoning Engine
- Controls timings of sending messages



- Smoothes EPA values calucated by the Calculator

Experiments - Parameter values used in laboratory experiments

Param.	Value	Defined in which component
n	10	EPA-Calc
$distance$	$\{-\infty, 0, 8, 40, 128, 160, +\infty\}$	EPA-Calc
$potency$	$\{-4.3, -4.3, 0, 1, 2, 4.3, 4.3\}$	EPA-Calc
$difference$	$\{-\infty, 0, 3.5, 17.5, 35, 70, +\infty\}$	EPA-Calc
$activity$	$\{-4.3, -4.3, -2, -1, 0, 4.3, 4.3\}$	EPA-Calc
$alpha$	0	Buffer
$timeout$	300	Buffer
$timeup$	1	Buffer
β_a^0	0.001	Updater
β_c^0	2.0	Updater
γ	$(100000, 1.0, 0.5)$	Updater
N	2000	Updater
f_a^0	$[1.5, 0.51, 0.45]$	Updater
f_c^0	Different in each test	Updater