SuPerCo

SuperCo
Data interpretation for subject monitoring

Mistis – 15 mars 2011

“SuPerCo”

Building a system that detects when a subject physiological state is alarming

System characteristics

- multi-sensors : accelerometers, heart rate and breath frequency measures ...
- adaptivity : to the subject, to the context
- robustness, fiability, security

Major challenges

- multivariate, asynchronous, noisy data
- data interpretation (ambiguity)
- alarming situation definition

Introduction

System proposal

- Multiple hypothesis management, no diagnostic
- 2 main abstraction levels (states and micro-scenarios) for hypothesis definition
- Introducing context-dependencies in the modelling problem
- Probabilistic approach for model learning (off-line) and computing confidence values for hypothesis (online)

Introduction

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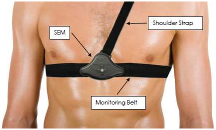
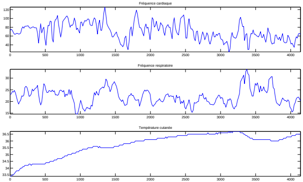
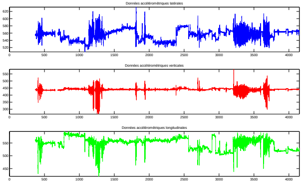
Observed data







$$Y_\varphi(t) = \begin{bmatrix} F_{card.}(t) \\ F_{br.}(t) \\ T_c(t) \end{bmatrix} \qquad Y_\alpha(t) = \begin{bmatrix} Y_{lat.acc.}(t) \\ Y_{vert.acc.}(t) \\ Y_{long.acc.}(t) \end{bmatrix}$$

$$Y(t) = (Y_\alpha(t), Y_\varphi(t)), \quad t = 1 \cdots T$$

States

- For each time t, $t = 1 \cdots T$, 2 types of states : physiological state $E_\varphi(t)$ and activity state $E_\alpha(t)$.
- **unknown, not observed**

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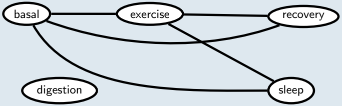
$E_\varphi(t)$

- Complex state : set of elementary states (ex: digestion et sleep)
- $E_\varphi(t) = \left[e_1(t) e_2(t) \cdots e_{M_\varphi}(t)\right]$, $\quad e_i(t) \in \{0, 1\}$, $i = 1 \cdots M_\varphi$
  Ex : $E_\varphi(t) = [011]$ si $e_1 =$basal, $e_2 =$sleep, $e_3 =$digestion
- theoretically, 2^{M_φ} possible states
- BUT, $\exists$ incompatibilities (sleep et exercise)
- and $N_\varphi < M_\varphi$ possibles states



Conditionning the model on the context (1)

Context

- what is the context ? A subject $\mathcal{P}$ in an environnement $\mathcal{E}$

$$\mathcal{C} = (\mathcal{P}, \mathcal{E})$$

- a priori known
- joint model :

$$p(Y_\alpha(1:T), Y_\varphi(1:T), E_\alpha(1:T), E_\varphi(1:T)|\mathcal{C}) = p(Y_\alpha(1:T), Y_\varphi(1:T)|E_\alpha(1:T), E_\varphi(1:T), \mathcal{C}) \times p(E_\alpha(1:T), E_\varphi(1:T)|\mathcal{C})$$

Conditionning the model on the context (2): state model

- homogeneous Markov chain

$$p(E_\alpha(1:T), E_\varphi(1:T)|\mathcal{C}) = \prod_{t=2}^{T} p(E_\alpha(t), E_\varphi(t)|E_\alpha(t-1), E_\varphi(t-1); \mathcal{C}) \times p(E_\alpha(1), E_\varphi(1)|\mathcal{C})$$

- independent chain transitions

$$\begin{aligned} P\left((E_\alpha(t), E_\varphi(t)) = (u,i)|(E_\alpha(t-1), E_\varphi(t-1)) = (v,j); \mathcal{C}\right) = \\ P(E_\alpha(t) = u|E_\alpha(t-1) = v; \mathcal{C})\ P(E_\varphi(t) = i|E_\varphi(t-1) = j; \mathcal{C}) \\ = \quad T_\alpha(E_\alpha(t-1) = i, E_\alpha(t) = j) \times T_\varphi(E_\varphi(t-1) = u, E_\varphi(t) = v) \end{aligned}$$

Conditionning the model on the context (3): observations model

- $Y_\alpha(1:T)$ and $Y_\varphi(1:T)$ are conditionally independent

$$\Rightarrow p(Y_\alpha(1{:}T), Y_\varphi(1{:}T)|E_\alpha(1{:}T), E_\varphi(1{:}T), \mathcal{C}) =$$
$$p(Y_\alpha(1{:}T)|E_\alpha(1{:}T), E_\varphi(1{:}T), \mathcal{C}) \times p(Y_\varphi(1{:}T)|E_\alpha(1{:}T), E_\varphi(1{:}T), \mathcal{C})$$

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- $Y(t)$: independent wrt. previous and future data and states

$$\Rightarrow p(Y(1{:}T) | E_\alpha(1{:}T), E_\varphi(1{:}T), \mathcal{C}) = \prod_{t=1}^{T} p(Y(t) | E_\alpha(t), E_\varphi(t), \mathcal{C})$$

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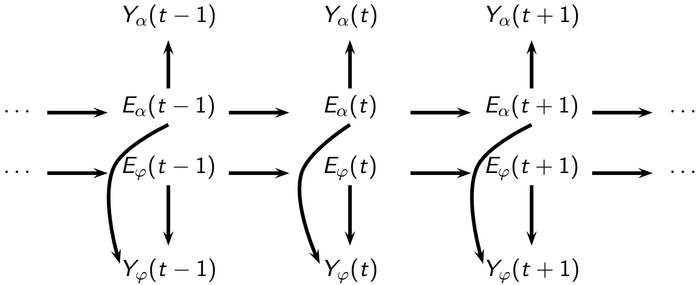
- $Y_\alpha(t)$ are physical measures $\rightarrow$ independency wrt. $E_\varphi(t)$ and $\mathcal{C}$

$$p(Y_\alpha(t) | E_\alpha(t), E_\varphi(t), \mathcal{C}) = p(Y_\alpha(t) | E_\alpha(t))$$

Conditionning the model on the context (4): graphical representation



$\Rightarrow$ Factorial HMM with two states chains

Data modelling

Which model for the data ?

$Y_\alpha(t)$

$$(Y_\alpha(t)|E_\alpha(t)=k) \sim \mathcal{N}_3\left(\mu_\alpha(k);\Sigma_\alpha(k)\right)$$

$$\boxed{\theta_\alpha = \left(\left\{\mu_\alpha(k),\Sigma_\alpha(k)\right\}, k = 1\cdots M_\alpha\right)}$$

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$Y_\varphi(t)$

- indirect states dependency via deterministic function: $h(E_\alpha, E_\varphi)$
  $(Y_\varphi(t)|E_\alpha(t)=k, E_\varphi(t)=u; \mathcal{C}) \sim \mathcal{N}_2(\mu_\varphi(\mathcal{C}, h(k,u)), \Sigma_\varphi(\mathcal{C}, h(k,u)))$
- $h(\cdot,\cdot)$, chosen so that : $h(E_\alpha, E_\varphi) \in \mathcal{H} = \{0 \cdots H\}$
  $\rightarrow$ may be viewed as “intensity” levels
- Introduction of physiological characteristics:

$$\mu_\varphi(\mathcal{C}, h) = \begin{bmatrix} m_c(\mathcal{C}, h) \\ m_b(\mathcal{C}, h) \end{bmatrix} = \begin{bmatrix} F_c^{max}(\mathcal{P}) - f_c(\mathcal{C}, h) \\ F_b^{basal}(\mathcal{P}) + f_b(\mathcal{C}, h) \end{bmatrix}$$

$$\Sigma_\varphi(\mathcal{C}, h) = \begin{bmatrix} \sigma_c(\mathcal{C}, h) & 0 \\ 0 & \sigma_b(\mathcal{C}, h) \end{bmatrix}$$

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$$\boxed{\theta_\varphi(\mathcal{C}) = \left(F_c^{max}(\mathcal{P}), F_b^{basal}(\mathcal{P}), f_c(\mathcal{C},h), f_b(\mathcal{C},h), \sigma_c(\mathcal{C},h), \sigma_b(\mathcal{C},h); \text{ for all } h\right)}$$

$$\theta = (\theta_\alpha, \theta_\varphi(\mathcal{C}))$$

Inference

Parameter identification

Maximum likelihood:

$$\hat{\theta}(\mathcal{C}) = \arg\max_{\theta} p(Y(1{:}T)|\theta;\mathcal{C})$$

- Numerical approach : EM-based
- Off-line process

Inference

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A posteriori state probability computation

$$p\left(E_\alpha(t){=}k|Y(1{:}t),\hat{\theta}(\mathcal{C});\mathcal{C}\right) = \sum_u p\left(E_\alpha(t){=}k, E_\varphi(t){=}u|Y(1{:}t),\hat{\theta}(\mathcal{C});\mathcal{C}\right)$$

$$p\left(e_j(t){=}1|Y(1{:}t),\hat{\theta}(\mathcal{C});\mathcal{C}\right) = \sum_k \sum_{u|u(j)=1} p\left(E_\alpha(t){=}k, E_\varphi(t){=}u|Y(1{:}t),\hat{\theta}(\mathcal{C});\mathcal{C}\right)$$

Preliminary results (1) : simulated data

- Man, 32 ans, $F_c^{rest} = 80$ bpm, $F_b^{basal} = 14$ breath/min
- $$f_c(\mathcal{P}, h) = \begin{cases} 10 & \text{if } h = 5 \\ 20 & \text{if } h = 4 \\ \cdots & \cdots \\ 50 & \text{if } h = 1 \\ \gamma(\mathcal{P}) & \text{if } h = 0 \end{cases}, \; f_b(\mathcal{P}, h) = \begin{cases} 0 & \text{if } h = 0 \\ \Delta & \text{if } h = 1 \\ 2\Delta & \text{if } h = 2 \\ \cdots & \cdots \\ 5\Delta & \text{if } h = 5 \end{cases}$$

  $\gamma(\mathcal{P}) = F_c^{max}(\mathcal{P}) - F_c^{rest}(\mathcal{P}), \; \Delta = \frac{60 - F_b^{basal}(\mathcal{P})}{5}$.
- $$F_c^{max}(\mathcal{P}) = \begin{cases} 220 - \text{age}(\mathcal{P}) & \text{for men} \\ 206 - 88\%\text{age}(\mathcal{P}) & \text{for women} \end{cases}$$
- Scenario :

t	$1 \cdots 200$	$201 \cdots 500$	$501 \cdots 600$	$601 \cdots 800$
$E_\alpha(t)$	inactive	medium mvt	inactive	inactive
$E_\varphi(t)$	basal	exercise	recovery	basal
$h(E_\alpha(t), E_\varphi(t))$	0	4	2	0

Preliminary results (1) : estimated parameters

situations	h	Model parameters											
		m_c	$\hat{m}_c$	m_b	$\hat{m}_b$	μ_α	$\hat{\mu}_\alpha$	σ_c	$\hat{\sigma}_c$	σ_b	$\hat{\sigma}_b$	Σ_α	$\hat{\Sigma}_\alpha$
basal inactive	0	80	79.96	14	13.98	$\begin{bmatrix} 560 \\ 440 \\ 580 \end{bmatrix}$	$\begin{bmatrix} 560.05 \\ 440.05 \\ 580.09 \end{bmatrix}$	4	3.80	2	1.97	$\begin{bmatrix} 5 & 0 & 0 \\ 0 & 5 & 0 \\ 0 & 0 & 5 \end{bmatrix}$	$\begin{bmatrix} 5.08 & 0 & 0 \\ 0 & 5.44 & 0 \\ 0 & 0 & 4.93 \end{bmatrix}$
exercise medium movement	4	168	168.52	50.8	50.86	$\begin{bmatrix} 560 \\ 440 \\ 580 \end{bmatrix}$	$\begin{bmatrix} 559.99 \\ 440.20 \\ 579.86 \end{bmatrix}$	15	14.63	8	8.61	$\begin{bmatrix} 30 & 0 & 0 \\ 0 & 30 & 0 \\ 0 & 0 & 30 \end{bmatrix}$	$\begin{bmatrix} 23.53 & 0 & 0 \\ 0 & 22.71 & 0 \\ 0 & 0 & 23.64 \end{bmatrix}$
recovery inactive	2	148	163.52	32.4	44.98	$\begin{bmatrix} 560 \\ 440 \\ 580 \end{bmatrix}$	$\begin{bmatrix} 560.05 \\ 440.05 \\ 580.09 \end{bmatrix}$	8	0.93	4	1.08	$\begin{bmatrix} 5 & 0 & 0 \\ 0 & 5 & 0 \\ 0 & 0 & 5 \end{bmatrix}$	$\begin{bmatrix} 5.08 & 0 & 0 \\ 0 & 5.44 & 0 \\ 0 & 0 & 4.93 \end{bmatrix}$

Preliminary results(2) : a posteriori probabilities for E_α

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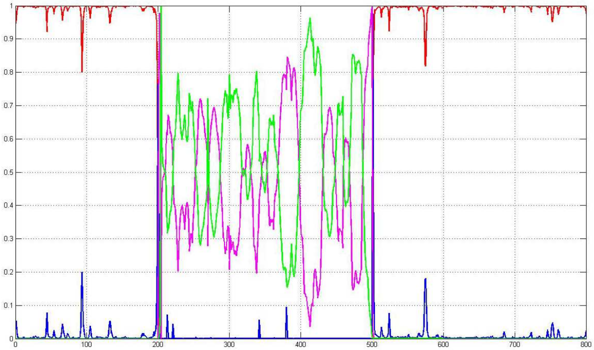
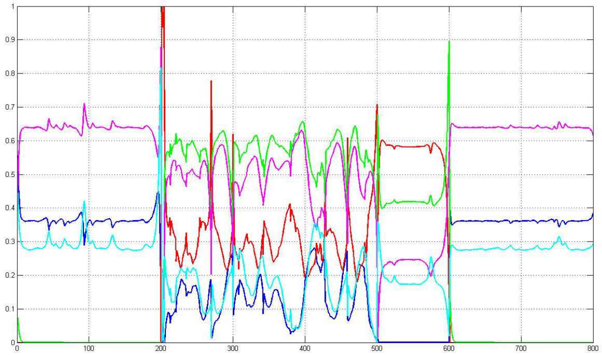
Observed data
States
Model within a context
Data models
Inference
Preliminary results
Conclusion

inactive : red ; light mvt : blue
medium mvt : magenta ; intense mvt : green



Preliminary results(3) : a posteriori probabilities for e_i

basal : blue ; exercise : red ; recovery : green
sleep : magenta ; digestion : cyan



Conclusions and perspectives

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- Preliminary results quite encouraging
- Parameter estimation: pb of state identifiability (h surjective)
- A posteriori probabilities: non-identifiability due to ambiguity $\Rightarrow$ multiple hypothesis management in the system (higher level)

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Perspectives

- Taking into account the identifiability pb in the estimation
- Real data validation
- Other physiological data models: skin temperature, O_2 saturation
- $h(E_\alpha, E_\varphi)$ function refinement ! with experts from TIMC
- More complex models (large number of states): variational methods for approximate computation