Consiglio Nazionale delle Ricerche

Occupancy pattern recognition with infrared array sensors: A Bayesian approach to multi-body tracking

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Problem: tracking of body-induced thermal signatures

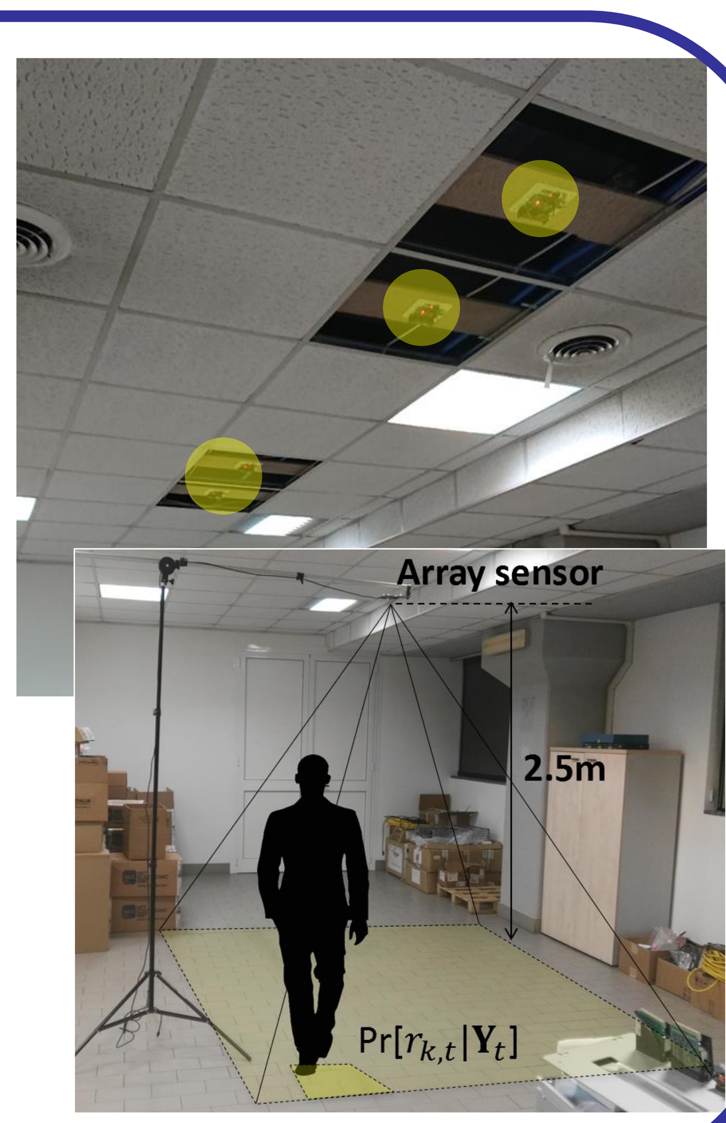
Thermal vision systems based on **low-cost IR array sensors** are becoming attractive in many smart living scenarios.

Thermal vision and related computing tools enable the possibility of analyzing body configurations, activities and motion patterns, without the being limited by **privacy issues** since no specific person can be recognized through **the analysis of thermal frames**

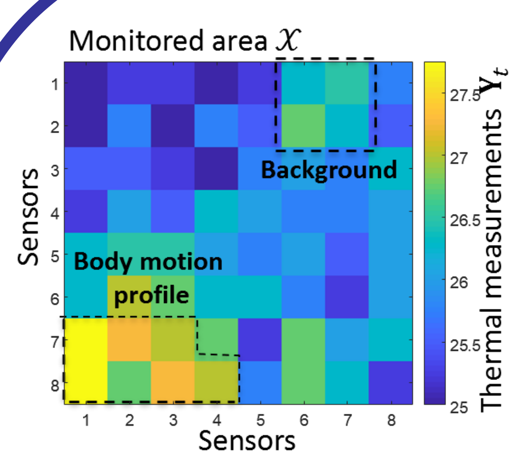
This paper proposes a Bayesian framework for recognition and discrimination of body motions based on real-time analysis of thermal signatures.

We propose to use of **low-resolution IR array sensors** for occupancy estimation. Such thermal sensors are typically **ceiling-mounted** (see picture on the right). In particular, we address the problem of **tracking the location of an arbitrary number of individuals** (i.e, targets) that can freely move inside the monitored area

The proposed toolkit learns a **statistical model** for the extraction of body-induced thermal signatures from noisy data; then it applies a **mobility model** for **tracking** multi-body motions in the area



Bayesian model learning

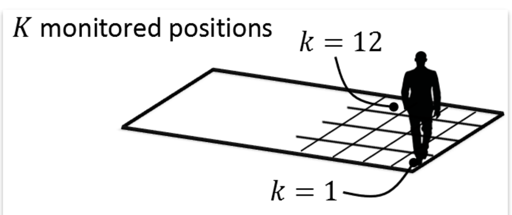


We consider a frame $\mathbf{y}_t$ of M received noisy temperature readings from the corresponding thermopile elemets of the array.

For occupancy pattern estimation, we divide the montored area into a grid of $K \leq M$ regions of interest.

We tackle the problem of estimating the occupancy in each region $\mathbf{r}_t = [r_{t,1}, ..., r_{t,k}, ..., r_{t,K}]^{\mathrm{T}}$, $r_{t,k} \in [0,1]$ by linear model

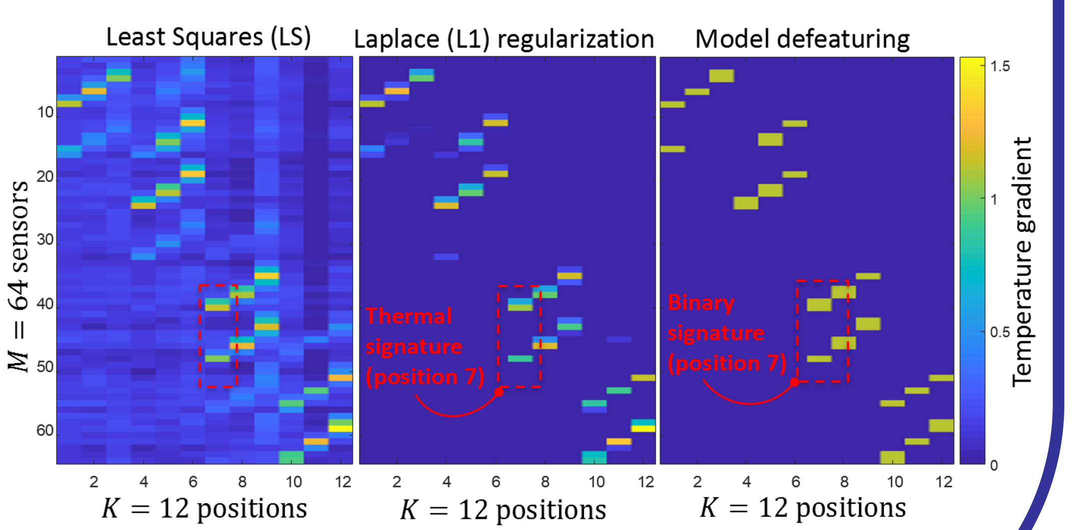
$$\mathbf{y}_t = \mathbf{H} \times \mathbf{r}_t + \mathbf{w}_t$$
$$\mathbf{w}_t \sim \mathcal{N}(\boldsymbol{\mu}, \mathbf{C})$$



$\widehat{\mathbf{H}}$: estimated model

Elements of matrix **H** are **sparse**, we thus use a **Laplace prior distribution** (Lasso-type regularization)

$$\widehat{\mathbf{H}} = \mathrm{argmax}_{\mathbf{H}} \sum_{i=1}^{N} \log \Pr\left[\mathbf{y}_t^{(i)} \mid \mathbf{r}_t^{(i)}; \mathbf{H}\right] + $$
$$+\lambda \sum_{m=1}^{M} \sum_{k=1}^{K} \log \Pr(H_{m,k})$$
$$\Pr(H_{m,k}) \propto \exp(-\sqrt{2}\,|H_{m,k}|)$$

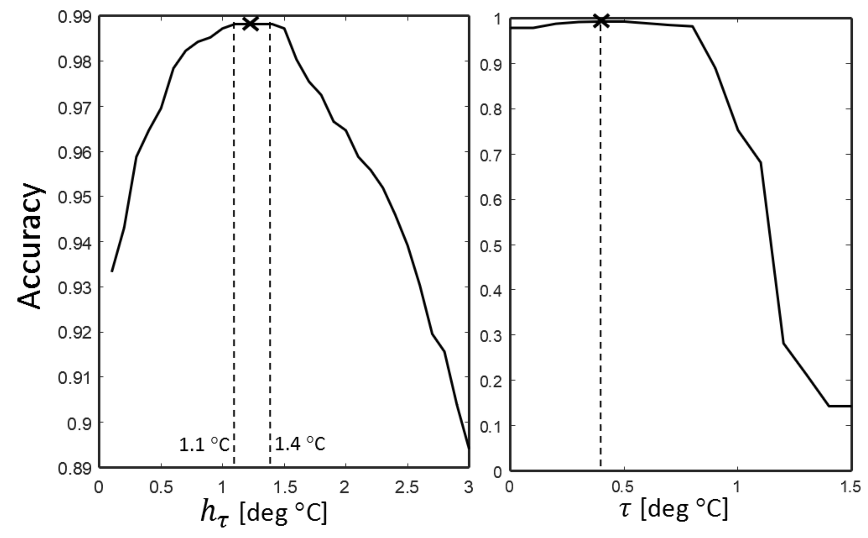


Bayesian filtering (tracking)

Model simplification is applied to suppress irrelevant (or small) thermal signature, to provide an estimate less sensitive to training impairments

$$\widehat{H}_{h,k}^{(\mathrm{S})} = \begin{cases} h_\tau, & \widehat{H}_{h,k} > \tau \\ 0, & \widehat{H}_{h,k} \leq \tau \end{cases}$$

$h_\tau = 1.1°\mathrm{C} \div 1.4°\mathrm{C}$.
$\tau < 0.4°\mathrm{C}$



Tracking of body occupancy is based on a-posterior probability

$$\Pr(\mathbf{r}_t \mid \mathbf{Y}_t) = \prod_{k=1}^{K} \Pr(r_{t,k} \mid \mathbf{Y}_t) \qquad \mathbf{Y}_t = [\mathbf{y}_1, ..., \mathbf{y}_t]^T$$

and we apply iterative Bayesian filtering

$$\Pr(r_{t,k} \mid \mathbf{Y}_t) \propto \Pr\left(\mathbf{y}_t \mid r_{t,k}; \widehat{\mathbf{H}}\right) \times \Pr(r_{t,k} \mid \mathbf{Y}_{t-1})$$

with a-prior probability updated iteratively

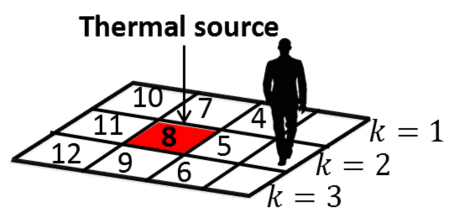
$$\Pr(r_{t,k} \mid \mathbf{Y}_{t-1}) = \int \Pr(\mathbf{r}_{t-1} \mid \mathbf{Y}_{t-1}) \Pr(r_{t,k} \mid \mathbf{r}_{t-1}) \mathrm{d}\mathbf{r}_{t-1}$$

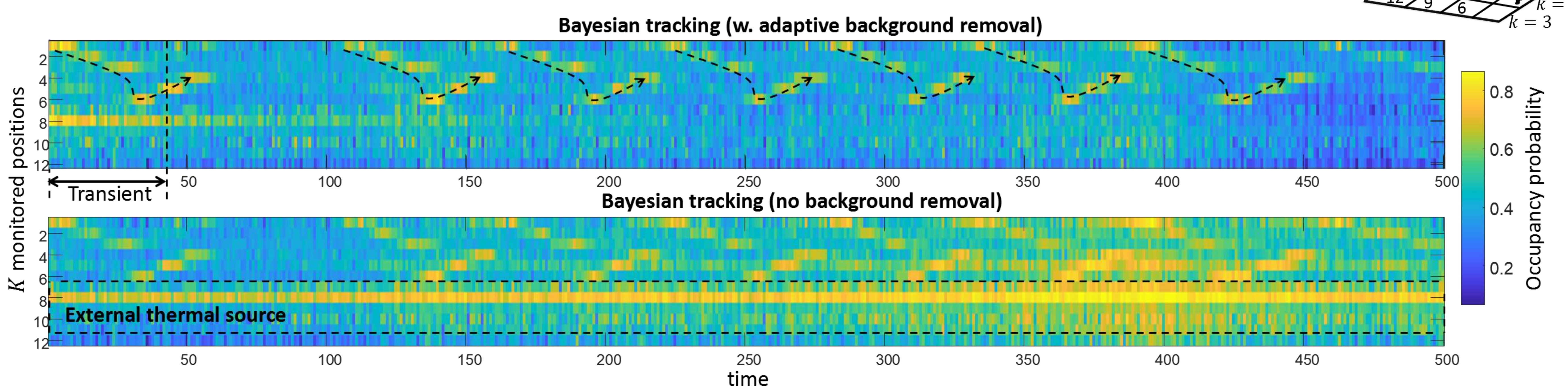
Transition probability (from **2D Gaussian random walk motion model**)

Experimental validation: occupancy pattern recognition

The use of a motion model as well as the processing of backlogs of thermal images prevent typical detection problems related with the temporal disappearance of the human body that are often experienced in practical ceiling mounting arrangements.
The Bayesian method is also integrated with an **adaptive background subtraction** method to filter out noisy thermal sources that are not induced by body movements

$$\boldsymbol{\mu}_k^{(t)} = \alpha \boldsymbol{\mu}_k^{(t-1)} + (1-\alpha)\,\mathbf{y}_{t,k} \qquad \mathbf{C}_k^{(t)} = \varsigma\, \mathbf{C}_k^{(t-T)} + \frac{(1-\varsigma)}{T-1} \sum_{i=0}^{T-1} \widetilde{\mathbf{y}}_{t-i,k} \widetilde{\mathbf{y}}_{t-i,k}^{\mathrm{T}} \qquad \widetilde{\mathbf{y}}_{t,k} = \mathbf{y}_{t,k} - \boldsymbol{\mu}_k^{(t)}$$





Ceiling mounted sensor

Experimental validation exploits **M=64 (8x8) sensor array. (Grid-EYE Panasonic).** Each sensor can monitori 2.5m sq. area, mounted on a 3m ceiling. Sampling is 100ms.

The area is divided into *k=12* areas.

A **fixed thermal source** (a small radiator) is deployed in region *k=8* to generate a localized and time-varying heat signature. **1-5 subjects are moving by following a repeated pattern.**

After a transient of 45 sec. the system is able to learn the new background and track the targets. Body tracking has accuracy of 97%