OCCUPANCY PATTERN RECOGNITION WITH INFRARED ARRAY SENSORS: A BAYESIAN APPROACH TO MULTI-BODY TRACKING

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ABSTRACT

Thermal vision systems based on low-cost IR array sensors are becoming attractive in many smart living scenarios. This paper proposes a Bayesian framework for recognition and discrimination of body motions based on real-time analysis of thermal signatures. Unlike conventional frame-based methods, the proposed approach exploits a statistical model for the extraction of body-induced thermal signatures and a mobility model for tracking multi-body motions inside an indoor area. This approach prevents typical detection problems and can be also used in presence of interfering thermal sources such as heaters, radiators and other thermal devices. The Bayesian method is verified experimentally for ceiling mounted sensors and shows high accuracy and robustness even in cases where thermal signatures are closer to the ambient temperature.

***Index Terms*—** Infrared Array Sensors, Bayesian filtering, Body Tracking, Passive Detection, Internet of Things

1. INTRODUCTION

The use of thermal sensors for human body sensing [1] is becoming attractive in many IoT-relevant scenarios, such as smart spaces [2, 3], assisted living [4, 5], and industrial automation [6]. Thermal vision and related computing tools enable the possibility of analyzing body configurations, activities and motion patterns, without being limited by privacy issues since no specific person can be recognized through the analysis of thermal frames. In addition to low invasiveness, IR (Infrared) arrays overcome [7] some problems related to vision sensors, since humans have a distinctive thermal profile compared to objects, and sensor data does not depend on light conditions. Here, we propose to use low-resolution thermal sensors for occupancy estimation. 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 thermal sensors used here consist of low-cost IR sensor arrays similar to [8, 9, 10] that are characterized

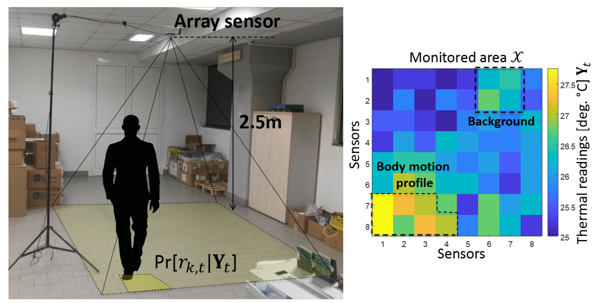

Fig. 1. Layout example and noisy temperature readings.

by a high temporal and spatial resolution. Signal processing methods are then applied to raw thermal measurements to obtain an occupancy estimate in real-time. Existing techniques are mostly based on frame-based computer vision approaches that consider time-slices (frames) of raw temperature measurements individually, and range from K-nearest neighbor (K-NN) [8, 10], decision trees [11, 12], Kalman filtering [13], support vector machines [3, 14] to adaptive thresholding [15]. A Bayesian technique has been proposed in [16], however the problem formulation is limited therein to a single IR sensor.

This paper focuses on the analysis, design and implementation of a Bayesian filtering tool that models body-induced thermal signatures, analyzes and tracks body movements through a sequence of frames. Compared to conventional frame-based methods [8] [9], 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. The space-time Bayesian filtering approach is able to track an arbitrary number of targets by considering both current and past raw thermal images and outputs the probability of occupancy in selected locations. 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 [15] that are often experienced in practical ceiling mounting arrangements. An adaptive background subtraction method is also adopted to filter out noisy thermal sources.

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2. SYSTEM MODEL

We introduce here a statistical model for the raw thermal data captured by the sensor array. This model can serve as a general framework for application to multi-sensor deployments and large IR arrays. In what follows, a ceiling-mounted sensor array is considered, being the most interesting and practical deployment scenario for smart-living applications. However, other placements might also fit as well. We consider a frame $\mathbf{y}_t$ of M received noisy temperature measurements $\mathbf{y}_t = [y_{t,1}, ..., y_{t,M}]^{\mathrm{T}}$ at time t that collects the temperature readings from the M thermopile elements (in 1D or 2D grid format). Focusing on occupancy pattern estimation, we divide the area $\mathcal{X}$ within the sensor array field-of-view into a grid consisting of $K \leq M$ physical regions of interest. Each region k (with $1 \leq k \leq K$) is defined over a 2D space $\mathcal{X}_k$ characterized by its barycenter $\overline{\mathbf{x}}_k$ used to drawn positioning information. We tackle the problem of estimating the occupancy in each region $\mathbf{r}_t = [r_{t,1}, ..., r_{t,k}, ..., r_{t,K}]^{\mathrm{T}}$ with $r_{t,k} \in [0, 1]$ that provides a binary information about occupancy at time t within the k-th region. Noisy temperature readings are assumed to depend linearly on the pattern $\mathbf{r}_t$ as

$$\mathbf{y}_t = \mathbf{H} \times \mathbf{r}_t + \mathbf{w}_t \tag{1}$$

where the $M \times K$ matrix $\mathbf{H}$ maps the thermal signatures (temperature increases) onto the corresponding positions of interest and $\mathbf{w}_t$ models the noisy background obtained in the empty environment. The background $M \times 1$ vector $\mathbf{w}_t = [w_{t,1}, ..., w_{t,M}]^{\mathrm{T}}$ conveys information about noisy heat-sources that are not caused by body movements but characterize the empty space. This is modeled here as multivariate Gaussian $\mathbf{w}_t \sim \mathcal{N}(\boldsymbol{\mu}, \mathbf{C})$ with average $\boldsymbol{\mu}$ and covariance $\mathbf{C}$.

2.1. Bayesian model learning

Learning of model parameters for body-induced heat signatures $\mathbf{H}$ and background/ambient temperature $\{\boldsymbol{\mu}, \mathbf{C}\}$ in (1) is based on the conditional maximum likelihood $\Pr[\mathbf{y}_t \mid \mathbf{r}_t; \mathbf{H}, \{\boldsymbol{\mu}, \mathbf{C}\}]$ estimator. Modeling of ambient temperature $\{\boldsymbol{\mu}, \mathbf{C}\}$ is based on thermal measurements in the empty space and estimation of covariance terms uses an L2 regularization. The presence of external thermal sources impair the body motion tracking as causing false or duplicated targets. Therefore, an adaptive background removal method is proposed and validated in Sect. 4. Heat signatures $\mathbf{H}$ are described in terms of temperature increases and are function of specific multi-body motion patterns. Therefore, it is reasonable to assume that the elements $H_{m,k}$ of matrix $\mathbf{H}$ are intrinsically sparse: to capture this effect, we force the linear coefficients of matrix $\mathbf{H}$ to have a Laplace prior distribution with zero mean and unit variance $\Pr(H_{m,k}) \propto \exp(-\sqrt{2}\,|H_{m,k}|)$. This Lasso-type regularization [17] is effective in modeling sparse heat signatures as observed in real data. We assume N labeled examples $\left(\mathbf{r}_t^{(i)}, \mathbf{y}_t^{(i)}\right)$, where each example $\mathbf{y}_t^{(i)}$,

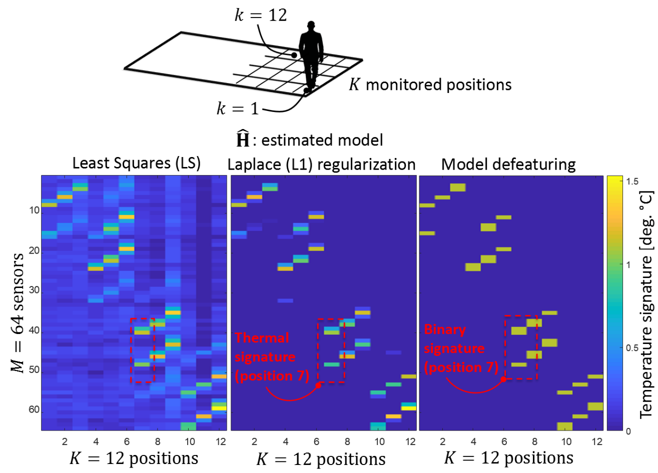

Fig. 2. Least-Squares (LS) vs. Lasso-type regularization and corresponding model simplification for model $\mathbf{H}$ estimation.

$i = 1, ..., N$, corresponds to a known occupancy pattern $\mathbf{r}_t^{(i)}$ during training. The model $\mathbf{H}$ is thus estimated as

$$\begin{aligned} \widehat{\mathbf{H}} = \operatorname{argmax}_{\mathbf{H}} \textstyle\sum_{i=1}^{N} \log \Pr\left[\mathbf{y}_t^{(i)} \mid \mathbf{r}_t^{(i)}; \mathbf{H}\right] + \\ + \lambda \textstyle\sum_{m=1}^{M} \sum_{k=1}^{K} \log \Pr(H_{m,k}) \end{aligned} \tag{2}$$

where λ is the regularization parameter. For Gaussian background, it is $\widehat{\mathbf{H}} = \operatorname{argmin}_{\mathbf{H}} \sum_{i=1}^{N} \left\| \widetilde{\mathbf{y}}_t^{(i)} - \mathbf{H} \times \mathbf{r}_t^{(i)} \right\|_{\mathbf{C}}^2 + \lambda \sum_{m=1}^{M} \sum_{k=1}^{K} |H_{m,k}|$ and equation (2) reduces to the LS method with $\widetilde{\mathbf{y}}_t^{(i)} = \mathbf{y}_t - \boldsymbol{\mu}$ being the noisy measurements after background $\boldsymbol{\mu} = [\mu_1, ..., \mu_M]^{\mathrm{T}}$ subtraction. $\|\mathbf{y}\|_{\mathbf{C}} = \mathbf{y}^T \mathbf{C}^{-1} \mathbf{y}$ denotes weighting by covariance $\mathbf{C}$. The regularization sets matrix $\mathbf{H}$ to have a sparse representation.

2.2. Model simplification

Model simplification is applied in this section to suppress small or irrelevant thermal signatures and, in turn, to provide an estimate $\widehat{\mathbf{H}}$ that is less sensitive to training impairments. Considering the k-th area, i.e., column k of matrix $\widehat{\mathbf{H}}$, the corresponding non-zero elements $\widehat{\mathbf{h}}_k = \left\{\widehat{H}_{h,k} : \forall h, \widehat{H}_{h,k} > 0\right\}$ reflect the subset $\mathbf{y}_{t,k} = \left\{y_{t,h} : \forall h, \widehat{H}_{h,k} > 0\right\}$ of the array elements that are more sensitive to the body movements inside k. These terms are, in turn, thermal signatures, or *features*, that correspond to a body moving in the considered area k. We apply a de-featuring stage where each thermal signature $\widehat{\mathbf{h}}_k$ is passed through an optimized binary function, namely $\widehat{\mathbf{h}}_k^{(\mathrm{S})} = \left\{\widehat{H}_{h,k}^{(\mathrm{S})}\right\}$ with

$$\widehat{H}_{h,k}^{(\mathrm{S})} = \begin{cases} h_\tau, & \widehat{H}_{h,k} > \tau \\ 0, & \widehat{H}_{h,k} \leq \tau \end{cases} \tag{3}$$

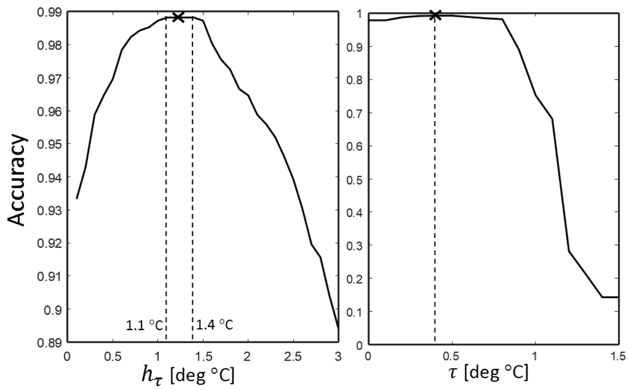

Fig. 3. Optimized threshold τ and body induced thermal signature h_τ for typical 3 m ceiling mounted sensors.

where h_τ models the average body-induced thermal increase compared to ambient temperature while τ is a sensitivity threshold. Assuming $K = 12$ positions, Fig. 2 (from left to right) compares the estimated model $\widehat{\mathbf{H}}$ using least-squares (without regularization), the resulting model using a Lasso-type prior and, finally, the corresponding model de-featuring. Considering typical ceiling mounted (3 m) sensors (see Sect. 4 for details) and a typical indoor room temperature (25°C), optimal threshold should be generally set as $\tau < 0.4$°C, while body-induced thermal increase falls in the range $h_\tau = 1.1°\mathrm{C} \div 1.4°\mathrm{C}$. Optimization is depicted in Fig. 3, where the optimal model parameter range has been selected to maximize the motion tracking accuracy.

3. BAYESIAN FILTERING

We assume that the binary vector $\mathbf{r}_t$, describing the occupancy pattern in the monitored area, is an Hidden Markov process. We track the body occupancy in each position by updating, for all monitored regions, the *a posteriori* probability conditioned on all observed temperature measurements $\mathbf{Y}_t = [\mathbf{y}_1, ..., \mathbf{y}_t]^T$ taken up to time t

$$\Pr(\mathbf{r}_t \mid \mathbf{Y}_t) = \prod_{k=1}^{K} \Pr(r_{t,k} \mid \mathbf{Y}_t). \tag{4}$$

Here, the Bayesian filtering approach is used to track the occupancy pattern iteratively and independently in each area. The *a posteriori* can be thus written as

$$\Pr(r_{t,k} \mid \mathbf{Y}_t) \propto \Pr\left(\mathbf{y}_t \mid r_{t,k}; \widehat{\mathbf{H}}\right) \times \Pr(r_{t,k} \mid \mathbf{Y}_{t-1}). \tag{5}$$

The conditional likelihood $\Pr\left(\mathbf{y}_t \mid r_{t,k}; \widehat{\mathbf{H}}\right)$ is based on model (1) while the estimated linear terms $\widehat{\mathbf{H}}$ are obtained by regularization according to (2) and model de-featuring (3) to

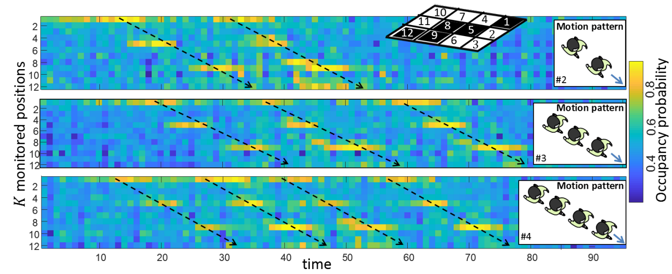

Fig. 4. Multi-body tracking: occupancy probability $\Pr(\mathbf{r}_t \mid \mathbf{Y}_t)$ when 2 up to 4 individuals are traversing the monitored area (see the trajectory on top), moving at random speed.

extract the body-induced thermal signatures $\widehat{\mathbf{h}}_k^{(\mathrm{S})}$. It is

$$\begin{aligned} \Pr\left(\mathbf{y}_t \mid r_{t,k} = 1;\ \widehat{\mathbf{H}}\right) &\sim \mathcal{N}(\widehat{\mathbf{h}}_k^{(\mathrm{S})} + \boldsymbol{\mu}_k, \mathbf{C}_k) \\ \Pr\left(\mathbf{y}_t \mid r_{t,k} = 0;\ \widehat{\mathbf{H}}\right) &\sim \mathcal{N}(\boldsymbol{\mu}_k, \mathbf{C}_k) \end{aligned} \tag{6}$$

where $\boldsymbol{\mu}_k$ and $\mathbf{C}_k$ are defined as $\boldsymbol{\mu}_k = \left\{\mu_h : \forall h, \widehat{H}_{h,k} > 0\right\}$ and $\mathbf{C}_k = \mathrm{E}_t[(\mathbf{w}_{t,k} - \boldsymbol{\mu}_k)(\mathbf{w}_{t,k} - \boldsymbol{\mu}_k)^T]$ while $\mathbf{w}_{t,k} = \left\{w_{t,h} : \forall h,\ \widehat{H}_{h,k} > 0\right\}$. In (5), the *a priori* probability $\Pr(r_{t,k} \mid \mathbf{Y}_{t-1})$ is updated iteratively as

$$\Pr(r_{t,k} \mid \mathbf{Y}_{t-1}) = \int \Pr(\mathbf{r}_{t-1} \mid \mathbf{Y}_{t-1}) \Pr(r_{t,k} \mid \mathbf{r}_{t-1}) d\mathbf{r}_{t-1}. \tag{7}$$

The transition probability $\Pr(r_{t,k} \mid \mathbf{r}_{t-1})$ is drawn from a motion model that tracks an arbitrary number of individuals. Based on occupancy information at time $t-1$, we first reconstruct the subset of occupied regions at time $t-1$, $\mathbf{K}_{t-1} = \{k :\ r_{t-1,k} = 1\}$. Then, we assign the position of each individual at time $t-1$ as the corresponding barycenter $\mathbf{x}_{t-1} = \overline{\mathbf{x}}_h$ with respect to the occupied region $h \in \mathbf{K}_{t-1}$ as

$$\Pr(r_{t,k} = 1 \mid \mathbf{r}_{t-1}) = \frac{\sum_{h \in \mathbf{K}_{t-1}} \int_{\mathcal{X}_k} \Pr(\mathbf{x}_t = \overline{\mathbf{x}}_k \mid \mathbf{x}_{t-1} = \overline{\mathbf{x}}_h) d\mathbf{x}_t}{\sum_{h \in \mathbf{K}_{t-1}} \int_{\mathcal{X}} \Pr(\mathbf{x}_t = \overline{\mathbf{x}}_k \mid \mathbf{x}_{t-1} = \overline{\mathbf{x}}_h) d\mathbf{x}_t}, \tag{8}$$

with $\Pr(r_{t,k} = 0 \mid \mathbf{r}_{t-1}) = 1 - \Pr(r_{t,k} = 1 \mid \mathbf{r}_{t-1})$. Notice that transition probability in (8) can be pre-computed for all $2^K \times 2^K$ combinations. Target movements in each region are modeled by a standard 2D Gaussian random walk [18] that rules the probability function $\Pr(\mathbf{x}_t \mid \mathbf{x}_{t-1})$ for each individual subject. For modeling random movements $\mathbf{x}_t = \mathbf{x}_{t-1} + \mathbf{v}_t$, we use a Gaussian driving process $\mathbf{v}_t$ corresponding to the maximum human body speed (typically 1 m/s). According to (5), for the iterative evaluation of $\Pr(r_{t,k} \mid \mathbf{Y}_t)$, a subject is detected in the k-th area if $\Pr(r_{t,k} \mid \mathbf{Y}_t) \geq \eta$, with threshold $\eta = 0.65$ calibrated from training. Finally, imaging over $\Pr(\mathbf{r}_t \mid \mathbf{Y}_t)$ in (4) can be used to detect motions.

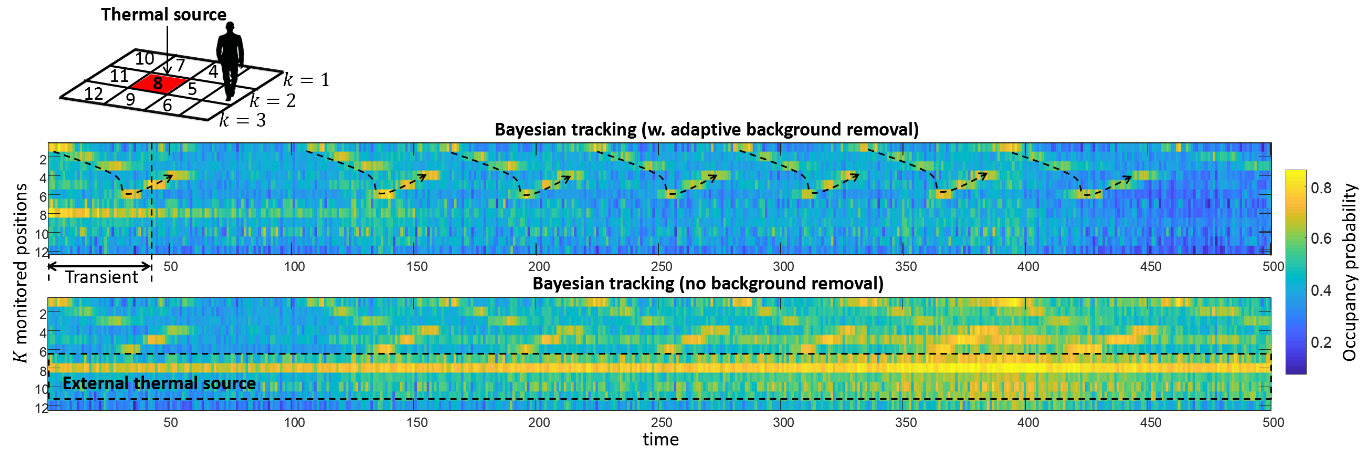

Fig. 5. Validation of Bayesian tracking tool with adaptive background removal. A fixed external thermal source is located in location 8 and generating a time-varying heat signature.

4. EXPERIMENTAL DATA AND VALIDATION

The experimental validation scenario exploits an 8×8 ($M = 64$) thermopile sensor array (Panasonic Grid-EYE model [10]) that can monitor a 2.5 m square area when mounted on a 3.0 m ceiling (faced down). Ceiling mounting is chosen being the most interesting and practical setup for IoT based applications. Fig. 1 sketches the layout of the detection area. The observed scene is divided up into $K = 12$ areas that form a regular grid of 0.5 m, while the propose Bayesian filtering tool is designed to evaluate the occupancy probabilities for all areas. The sensor array is configured for a sampling period equal to $\triangle t = 100$ ms and to detect absolute temperatures $\mathbf{y}_t$ by IR measurements modeled as in (1). During initialization, the system performs the estimation of the background parameters $\boldsymbol{\mu}_k$ and $\mathbf{C}_k$ in (6) for each location k. Then eqs. (1)-(3) are used to identify the body-induced thermal signatures $\widehat{\mathbf{h}}_k$ ($\lambda = 41$ is used for optimization). Finally, Bayesian filtering is used for real-time evaluation of unknown (unlabeled) data. For performance evaluation, we deployed also labeled landmarks in selected positions.

In Fig. 4, we show the performance evaluation of the body motion tracking system in a scenario with close body occupants ranging from 2 to 4 and moving according to the pattern illustrated in the superimposed sub-figures. Considering the monitored regions and their locations, the sensor can track people with an accuracy of about 0.5 m. Overall, detection and discrimination of occupancy within the K selected regions has high accuracy, greater than 99%, that is in line with typical requirements of smart-home applications.

A well-known limitation of thermal vision systems is their sensitivity to ambient thermal sources [12]. These sources impair human body tracking causing duplicates and false alarms as they can temporarily obscure body motions close by. Given that thermal sources are typically slowly varying compared to body motions, we apply a re-estimation of the parameters $\boldsymbol{\mu}_k$ and $\mathbf{C}_k$, that are used for each region k in the conditional likelihoods (6), by using a multivariate exponentially weighted moving average (MEWMA) and covariance matrix (MEWMC) [19], respectively. At time t, parameters $\boldsymbol{\mu}_k = \boldsymbol{\mu}_k^{(t)}$ and $\mathbf{C}_k^{(t)}$ are defined by recursion as $\boldsymbol{\mu}_k^{(t)} = \alpha \boldsymbol{\mu}_k^{(t-1)} + (1-\alpha)\,\mathbf{y}_{t,k}$ and $\mathbf{C}_k^{(t)} = \varsigma\,\mathbf{C}_k^{(t-T)} + \frac{(1-\varsigma)}{T-1}\sum_{i=0}^{T-1} \widetilde{\mathbf{y}}_{t-i,k}\widetilde{\mathbf{y}}_{t-i,k}^{\mathrm{T}}$, where $\widetilde{\mathbf{y}}_{t,k} = \mathbf{y}_{t,k} - \boldsymbol{\mu}_k^{(t)}$ and $T = 5$ samples. The smoothing constants $\alpha = 0.99$ and $\varsigma = 0.995$ are used to *tune* to different changes caused by typical devices (e.g., air conditioners, heaters and radiators). In Fig. 5, we validate the proposed Bayesian tracking tool with adaptive background removal. A fixed thermal source (e.g., a small radiator) is deployed within the region $k = 8$ where it generates a localized but time-varying heat signature. A human body is moving by following a given (repeated) pattern. After a transient period of about 45 samples (4.5 s), the system is effectively able to learn the new background and filter out the external source. Body tracking is still accurate (97%) in the surrounding of the locations $k = 4, 5, 6$ close to the area $k = 8$, as combining frame based detection with the motion model shown in (8).

5. CONCLUDING REMARKS

This paper proposes a Bayesian tool for tracking multiple bodies through real-time analysis of thermal signatures extracted from an IR sensor array. The proposed statistical model is validated experimentally to represent body-induced thermal signatures. Bayesian filtering combined with adaptive background subtraction is an effective tool even in presence of bodies moving close to ambient thermal sources.

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