# Approximation of Spatial and Temporal Temperature Behavior for Indoor Devices based on Thermal Recordings

Nicolaj Kirchhof
Robotics Research Institute, Dortmund, Germany. Email: nicolaj.kirchhof@tu-dortmund.de

***Abstract*—Exploiting the natural thermal radiation of humans is an elegant method to provide position information in indoor environments. The only drawback is that every object with a temperature greater then the ambient temperature is a source of disturbance. Such objects are typically devices like TV screens, heaters or computers. A robust thermal infrared localization system has to handle the noise produced by these sources in order to work in real world environments.**

**To handle radiation from these devices their influence on the localization has to be determined. Since the development of the localization system is largely based on simulations, an accurate description is needed. In this paper, a method is presented to approximate the temporal and spatial behavior of indoor devices. The method is based on thermal recordings and uses a separated spacial and temporal approximation. The first is based on clustering to find object regions with similar temporal behavior and the second on b-spline curve fitting to find a smooth representation of the temporal behavior. Furthermore, the method was applied to recordings conducted for different ambient temperatures in order to calculate a common description.**

## I. Introduction

Thermal infrared localization (ThILo) exploits the natural thermal radiation of humans to estimate their position in indoor environments. The localization is based on thermopile sensor nodes, which measure the angle of arrival (AOA) of heat sources within their field of view (FOV). The AoA of multiple Thermopiles can be used to calculate the position of a heat source by triangulation. Furthermore, the localization of multiple heat sources is possible with advanced localization filters [1], [2].

Most of the development progress in single und multiple target localization was done using simulated thermopile measurements provided by a self developed infrared simulation environment (IrSE) [3]. The IrSE allows a 3d representation of indoor scenes, whereas scenes and objects are stored and loaded using the Collada description format [4]. To simulate movements, the IrSE offers a basic set of animation techniques, which are limited to the ones that can be defined in Collada. These techniques can be applied to any simulation parameter e.g. the $x$, $y$ and $z$ position of a simulation object can be animated over time in order to simulate a movement.

Until now, the IrSE was solely used to simulate an empty room with one ore more moving heat sources to support the development of multi target filtering. Now, with an approved method to calculate the position of up to three heat source within this scene, the work will focus on testing the impact of sources of disturbance (SOD) on the localization. SOD are all artificial heat sources in the surveillance region with a temperature $> 10K$ above the ambient Temperature, e.g. devices like TV screens, computers or heaters.

Their common property is that they are not active all the time, instead a device is switched on at some point, then its temperature increases until its working temperature is reached. The working temperature is kept until the device is switched off and its temperature decreases to the ambient temperature.

The approximation of this unique behavior has a special focus because it might be a key to identify a SOD. In contrast to physical simulation environments like [5], [6] that need a detailed description of the object materials, it was not the goal to calculate the exact physical representation of the heat transfer, but to provide a valid approximation for the IrSE.

Therefore, this paper introduces a method based solely on a thermal recording of the device behavior. The purpose is to compute parameters that can be used to easily define a 3d representation of the real world device. Since it is unknown if the parameters holds for different ambient temperatures, approving experiments where conducted.

The paper is structured as follows, first a method for the spatial approximation is presented. Based on it, the temporal approximation is described in Section III, followed by the experimental results in Section IV. At last, a conclusion is drawn in Section V.

## II. Spatial approximation

The goal of the spatial approximation is to reduce the spatial resolution by calculating a minimum number of object regions with a similar temporal behavior. As a criteria for the similarity the temperature differences based on the accuracy of the thermal camera. For a single thermography image of the recording this can be stated as a data separation problem very similar to image processing segmentation problems, where regions of different color have to be separated. A Well-known class of algorithms that can be used for this task are clustering algorithms, which try to separate an input vector of data in a predefined number of clusters [7]. When the number of clusters is not known in advance and a minimum number of clusters based on a cluster criteria is needed, it can be found using an iterative search with a increasing number of clusters. The search ends either when a criteria is fulfilled for each cluster or a predefined maximum number of iterations is exceeded.

In order to find a valid clustering of an thermal image a criteria based on the temperature accuracy of the thermography camera was introduced. A calculated cluster was defined to be valid if the standard deviation of its pixel does not exceed a value of 2°K. With an iterative search that starts with a min number of two clusters and increases the number whenever no valid kmeans clustering was found. The criteria made it possible to calculate the minimum number of clusters for a single thermal image. Due to the spatial distribution of heat, these clusters where in most cases found to be coherent regions within the image.

Now, to find a minimum number of ROI with a valid criteria over the whole recording, a reference image had to be provided as input for the clustering algorithm. In order to suppress the background noise and to focus the clustering on the SoD within this image, the pixel by pixel difference of two normalized images where used. One of the images represented the mean pixel values over a timespan where the SOD had is highest temperature, whereas the other one represented the same values for a timespan where the object temperature was similar to the ambient temperature. The resulting image now expressed the increase in temperature for every pixel during the recording, whereas the object was well separated from the background.

Combining the use of difference images with the iterative K-Means search, it was possible to extract the minimum number of regions with a valid criteria over the whole time series.

## III. Temporal approximation

After the object regions were determined, a time series was computed for each region, which contained the mean of the regions pixel temperature values for every frame of the recording. As result a set of region descriptions $R = \{r_1, r_2, ..., r_n\}$ where stated,whereas every region

$$r_k = \begin{bmatrix} T & TP \end{bmatrix} = \begin{bmatrix} t_1 & tp_1 \\ \cdots & \cdots \\ t_m & t_m \end{bmatrix} \tag{1}$$

is a matrix of $m$ time $t$ and temperature $tp$ tuples.

In order to extract the underlying temporal object behavior from the region description, a curve fitting approach with respect to the Collada supported curve animations was used. As curve representation the cubic B-Spline interpolation was choosen because it allows a smooth representation of two dimensional data with an accuracy that can be refined by adding supporting points (SP).

Colladas B-Spline interpolation method is usually used to represent smooth trajectories for a movement. It is stated as

$$W^j(s) = \frac{1}{6} s M P^j \tag{2}$$

whereas $s = \begin{bmatrix} s^3 & s^2 & s & 1 \end{bmatrix}, s \in [0, 1]$ is the interpolation value that, multiplied with the weighting matrix $M$, calculates the weights that are applied to the SP $P^j = [P_x^j \ P_y^j]$. The number $q$ of connected splineparts depends on the number of defined SP. Furthermore, with $p_i \in P$ and $p_i = [x_i \ y_i], 0 \leq i \leq c$ being the matrix of all SP, the SP for the spline part $j$ can be stated as

$$P^j = \begin{bmatrix} x_{j-1} & y_{j-1} \\ x_j & y_j \\ x_{j+1} & y_{j+1} \\ x_{j+2} & y_{j+2} \end{bmatrix}. \tag{3}$$

Additionally, the overall number of spline parts is $q = c - 3, c \geq 4$.

As result of equation 2 a number of points $w^j(s) = [w_x^j(s) \ w_y^j(s)]$ along the B-Spline are calculated, whereas all points are within the convex hull span by $P^j$. Additionally, on the whole spline a two times derivable continuity is kept.

In order to use the B-Spline representation for a cubic function approximation it has to be shown that it is possible to express $w_y^j(s)$ dependent on $w_x^j(s)$. It can be shown that these dependencies can be fulfilled using a suitable choice of SP.

In detail, the SP have to be chosen equidistant along the $x$ dimension with $x_{i+1} = x_i + \Delta$. Now equation 2 can be simplified along this dimension.

$$\begin{aligned} w_x^j(s) &= \frac{1}{6} \begin{bmatrix} s^3 \\ s^2 \\ s \\ 1 \end{bmatrix}^T \begin{bmatrix} -1 & 3 & -3 & 1 \\ 3 & -6 & 3 & 0 \\ -3 & 0 & 3 & 0 \\ 1 & 4 & 1 & 0 \end{bmatrix} \begin{bmatrix} x_j - \Delta \\ x_j \\ x_j + \Delta \\ x_j + 2\Delta \end{bmatrix} \\ &= \frac{1}{6} \begin{bmatrix} s^3 \\ s^2 \\ s \\ 1 \end{bmatrix}^T \begin{bmatrix} x_j(-1+3-3+1) + \Delta(1-3+2) \\ x_j(3-6+3) + \Delta(-3+3) \\ x_j(-3+3) + \Delta(3+3) \\ x_j(1+4+1) + \Delta(-1+1) \end{bmatrix} \\ &= \frac{1}{6} [s^3 \ s^2 \ s \ 1] \begin{bmatrix} 0 \\ 0 \\ 6\Delta \\ 6x_j \end{bmatrix} \\ &= s\Delta \ x_j \end{aligned} \tag{4}$$

Using this result, the weighting factors $h_y^j$ of $w_y^j$ can be stated dependent on $w_x^j$ as

$$h_y^j(w_x^j) = \frac{1}{6} \begin{bmatrix} \Delta^{-3}(w_x^j - x_j)^3 \\ \Delta^{-2}(w_x^j - x_j)^2 \\ \Delta(w_x^j - x_j) \\ 1 \end{bmatrix}^T M \tag{5}$$

and finally the $w_y^j$ can be stated as

$$w_y^j(w_x^j) = h_y^j(w_x^j) \begin{bmatrix} y_{j-1} \\ y_j \\ y_{j+1} \\ y_{j+2} \end{bmatrix} \tag{6}$$

In order to calculate a appropriate number of SP, a convenient accuracy criteria had to be determined. Once more, the camera accuracy was taken into account and the criteria was defined as

$$w_y^j(t_i) \leq tp_i \pm 2°\mathrm{K}, \forall i. \tag{7}$$

The curve was now approximated using an iterative search strategy, starting with $c = 4$ and increasing this number until the criteria was fullfiled.

In each step the tuples $r_k$ where fit to a spline $W$. Therefore, at first the distance $\Delta$ between the $x$ values of the SP was calculated to

$$\Delta = \frac{t_m - t_1}{q}. \tag{8}$$

Then the $x$ values where determined with

$$x = \begin{bmatrix} t_1 - \Delta \\ t_1 \\ t_1 + \Delta \\ \vdots \\ t_1 + (c-2)\Delta \end{bmatrix}. \tag{9}$$

Using equation 6 the weights for all SP where calculated as

$$H(T) = \begin{bmatrix} h_y^1(T) & & \\ & \ddots & \\ & & h_y^q(T) \end{bmatrix} \tag{10}$$

and a linear optimization problem was stated as

$$\parallel H(T)Y - TP \parallel_{min}, \tag{11}$$

which was solved using a least squares approximation.

## IV. Experimental results

To test the developed method, four different devices where analyzed. Therefore, at first the temperature behavior was recorded using a tripod mounted Flir A20 thermography camera [8]. The camera was positioned at 1m distance in from of the SOD and kept static in this position throughout the recording. The latter was conducted as a separate record of the increasing and decreasing temperature behavior resulting from switching the object on and off. Since the exact durations of these behaviors where unknown, both records where initially taken over 4h time period with the camera provided framerate of 25hz.

The resulting spatial approximation was visually validated in regard to its purpose: to state a small number of regions that can easily be defined in a 3d model. The analized devices where a monitor, a small pc, a heating plate and a coffee maker. In figure 1 the resulting regions for the first three objects are presented. It can be seen that the number of calculated regions is less then five and the regions are spartially coherent.

In contrast to the good results for the first three objects that where calculated with the spatial approximation, the approximation failed for the coffee maker. A manual evaluation of this objects temporal bevavior show that the usage of difference images made it impossible to find regions with a valid criteria. In detail, the filter has almost the same temperature at the start and end of the coffee making process. Furthermore, the overall temperature is greatest at the end of the process due to the hot coffee pot which leads to an invalid input to the clustering algorithm since the temporal behavior of the filter is not considered.

TABLE I
CALCULATED NUMBER OF REGIONS AND SUPPORTING POINTS.

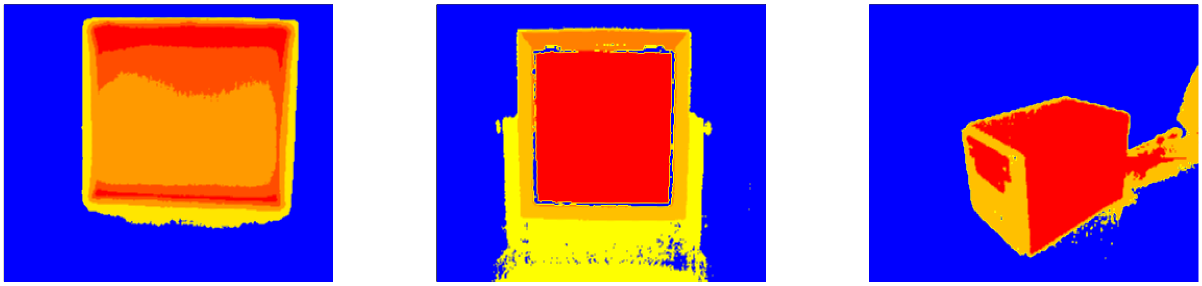
| Object | # Regions | # SP per region |
|---|---|---|
| Heating plate | 4 | 4, 4, 5, 6 |
| Shuttle PC | 2 | 4, 4 |
| TFT | 4 | 4, 4, 4, 6 |

TABLE II
HEATING PLATE REGIONS FOR DIFFERENT TEMPERATURES

| $\Delta$ ambient temperature | Region | Mean |
|---|---|---|
| $23,5°\mathrm{C} - 20°\mathrm{C} = 3,5°\mathrm{C}$ | | |
| | 1 | 3,7434 °C |
| | 2 | 3,2218 °C |
| | 3 | 3,3415 °C |
| | 4 | 3,7908 °C |
| | 5 | 3,4644 °C |
| $23,5°\mathrm{C} - 15°\mathrm{C} = 8,5°\mathrm{C}$ | | |
| | 1 | 9,5216 °C |
| | 2 | 7,8571 °C |
| | 3 | 8,4237 °C |
| | 4 | 9,1875 °C |
| | 5 | 8,1687 °C |
| $20°\mathrm{C} - 15°\mathrm{C} = 5°\mathrm{C}$ | | |
| | 1 | 5,7782 °C |
| | 2 | 4,6352 °C |
| | 3 | 5,0823 °C |
| | 4 | 5,3968 °C |
| | 5 | 4,7043 °C |

Nevertheless, the temporal approximation was calculated based on the calculated regions of the other objects. Exmplary the results for the heating plate are shown in Figure 2. Here the calculated splines are plottet in front of the $r_i$ tuples for all regions. From table I it can be seen that at most six supporting points are calculated for a valid approximation based on the stated criteria.

In order to evaluate the approximated behavior at different ambient temperatures the same blsehavior was recorded for three different ambient temperatures. Then, the spatial approximation was conducted for one of the recordings. The resulting regions where verified for the other recordings and the splines where calculated for each region. For the regions of the heating plate while warming, the results are shown in table II. Here the mean of the differences between the calculated splines of different ambient temperatures are given. It can be seen that the differnce is in range of the ambient temperature offset.



(a) Monitor (b) Heating plate (c) Shuttle PC

Fig. 1. Results of the spatial approximation for three different objects. Each color represents a calculated region for the object. For the monitor and the heating plate four distinct regions where calculated whereas the spatial approximation of the shuttle PC resulted in two object regions.

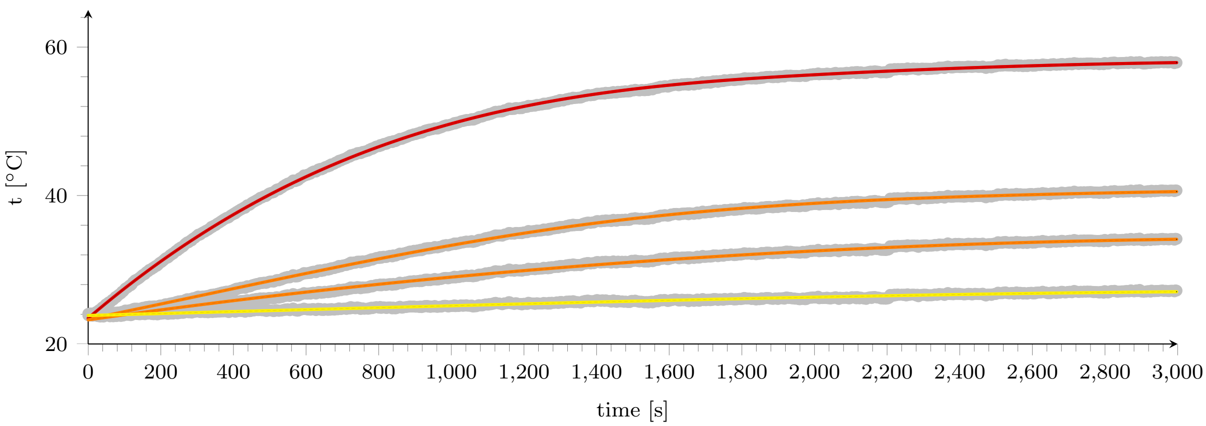



Fig. 2. Results of the temporal approximation for the four calculated heating plate regions. The spline approximation where colored to match the regions color in figure 1(b), wheras the gray 'background' of each spline is a plot of the evaluated region means.

## V. Conclusion

In this paper a method was proposed that uses a spatial and temporal approximation to simplify the temperature behavior that arises when indoor devices are switched on or off for a infrared simulation environment. The method is based on a thermography recording of the device and uses a spatial and temporal approximation that leads to a functional description of the temperature behavior over time for predetermined device regions.The results show that the method can be used as proposed for most devices.

The full paper will additionally include a comparison of real world and simulated thermopile measurements and localization results in order to determine the exact accuracy of the approximation. Furthermore, a detailed survey on the influence of the ambient temperature and the temporal approximation will be added.

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