Low-Resolution Overhead Thermal Tripwire for Occupancy Estimation

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Abstract

Smart buildings use occupancy sensing for various tasks ranging from energy-efficient HVAC and lighting to space-utilization analysis and emergency response. We propose a people counting system which uses a low-resolution thermal sensor. Unlike previous people-counting systems based on thermal sensors, we use an overhead tripwire configuration at entryways to detect and track transient entries or exits. We develop two distinct people counting algorithms for this configuration. To evaluate our algorithms, we have collected and labeled a low-resolution thermal video dataset using the proposed system. The dataset, the first of its kind, is public and available for download. We also propose new evaluation metrics that are more suitable for systems that are subject to drift and jitter.

1. Introduction

Occupancy sensing is a key technology for smart buildings of the future [2], [10], [8]. The knowledge of where and how many people are in a building enables, among others, smart HVAC control to save energy, space management to reduce rental costs and enhanced security, (e.g., fire, flooding, active shooter) [4]. Over the years, several people-counting systems have been proposed leveraging various sensing modalities, e.g., surveillance cameras, MAC address trackers, WiFi signal measurement, CO₂ sensors and thermal sensors [5], [6], each with its own deficiencies. For instance, surveillance cameras may not be acceptable in scenarios where privacy is expected, MAC address trackers require people to carry a networked device, WiFi signal measurement is sensitive to EM interference and unreliable for crowds of people, while CO₂ sensors have delayed reaction times due to slow mixing of gases. On the other hand, thermal sensors do not suffer from any of these issues.

To date, people-counting methods using low-resolution thermal sensors have focused on assessing the state of a room’s interior [2], [12], [1]. Such methods can be effective for small rooms, but in case of a large room the field of view (FOV) of a low-resolution thermal sensor might not be sufficient to capture all people in the room. In this scenario, multiple sensors are needed but this increases the cost, complexity of installation and requires complex processing to avoid overcounts due to FOV overlap.

In contrast, we propose to count people using a single low-resolution thermal sensor mounted above every entry/exit point of a room (Fig. 1) and develop a computational methodology to accomplish this. Regardless of room size, such thermal tripwires can independently detect people entering/exiting a room and jointly estimate the occupancy (state) of the room. In contrast to past methods, our approach is not frame-based but event-based, that is a people count is updated only upon the completion of a door event.

The approach we propose consists of three steps: background subtraction, event detection and event classification. In the first step, we detect “warm” pixels via a probabilistic background-temperature model based on Running Gaussian Average [13]. Since this model does not leverage spatial coherence of temperature, we combine it with a Markov Random Field (MRF) model [7] to produce high-temperature blobs. In the second step, based on background/foreground separation, we detect door events. In a baseline version, we assume that one person passes through the door at a...
time and we treat all foreground pixels as associated with this person. In order to handle wider doors and multiple people, we develop an enhanced algorithm that identifies high-temperature blobs and tracks them. In the third step, we classify each event as an entry or exit based on the direction of blob movement. To validate the performance of our algorithms, we have collected and manually labeled a dataset of thermal sequences covering various scenarios, including challenging edge cases. This dataset, the first of its kind, is public and available for download. We evaluate our algorithms on this dataset and show that while both proposed algorithms work equally well in normal scenarios the enhanced algorithm outperforms the baseline algorithm on edge cases.

To summarize, our paper makes several contributions. First, we believe this is the first work to develop and systematically study the overhead virtual tripwire configuration of a low-resolution thermal sensor for people counting. Second, we develop and validate two distinct people-counting algorithms based on low-resolution thermal data that are capable of handling challenging edge cases. Third, this work makes available to the research community a dataset of thermal sequences with manual annotations of entries into and exits from a room. Finally, we propose new metrics that provide a more meaningful evaluation of performance for systems that suffer from jitter and cumulative errors due to drift.

2. Related Work

Erickson et al. [3] proposed a people-counting system, called POEM, for energy management in buildings using a combination of video cameras in hallways and PIR sensors in rooms. Data coming from the camera and PIR networks are fused to estimate the people count.

ThermoSense [2] is the first system, to the best of our knowledge, that uses thermal sensors for people counting. However, unlike in our thermal-tripwire approach, each of its sensor’s FOV must cover the whole room to “see” all room occupants. ThermoSense estimates occupancy for each frame in three main steps: background subtraction, feature extraction, and people-count classification. The background subtraction is similar to that of ours; each pixel’s temperature is modeled by mean and standard deviation. A set of features are extracted from foreground/background segmentation, namely: the number of foreground pixels, the number of connected components, and the size of the largest connected component. These features are used to estimate occupancy by means of linear regression, kNN classification or neural network. In addition to thermal sensors, ThermoSense uses PIR sensors to detect whether a room is empty or not. This helps smooth out raw estimates and update the background model. Tyndall et al. [12] use a 16 × 4 Melexis sensor.

Amin et al. [1] proposed a people-counting system that uses a video camera and a thermal sensor both pointed inside a room, unlike in our approach. The use of two imaging modalities is meant to improve system robustness, e.g., in case of illumination variations. The counts are estimated separately using camera images and thermal frames and then linearly combined into a final people-count estimate.

3. Methodology

In our approach, we analyze consecutive thermal frames captured by a sensor mounted above a door (Fig. 1) in three steps: (1) background subtraction to first detect the presence of one or more people in the FOV of the sensor; (2) event detection to identify the beginning and end of entry or exit events spanning multiple frames; and (3) event classification as an entry or exit (Fig. 2). These three steps are discussed in detail below.

3.1. Background Subtraction

In this step, our goal is to separate the pixels that correspond to a human body from those that belong to the background (floor, walls, other surroundings). Since the system is designed for indoor people counting, it is reasonable to assume that a person is warmer than the background. Despite the difference between body temperature and room temperature, a single global threshold cannot reliably distinguish between them due to natural variations in people and indoor environments. In our approach, instead of thresholding temperature values, we model the background temperature of each pixel by a Gaussian pdf and apply a threshold to the temperature probabilities. Let $T_n(x)$ denote the temperature value of a pixel at location $x$ in frame $n$. We use the Running Gaussian Average (RGA) model [9], [11] to update the mean $\mu_n(x)$ at every background location $x$ as follows:

$$
\mu_n(x) = 1(T_n(x) \epsilon B) \left[ \alpha T_n(x) + (1 - \alpha)\mu_{n-1}(x) \right] + 1(T_n(x) \epsilon F) \mu_n(x)
$$

where the sets of background and foreground pixels are denoted by $B$ and $F$, respectively, $1(\cdot)$ is an indicator function.
and $0 < \alpha < 1$ is a weight controlling recursive update of the mean. We model the probability that a pixel at $x$ belongs to the background as follows:

$$P_B(T_n[x]) = \mathcal{N}(T_n[x] - \mu_n[x], \sigma)$$ (2)

where $\mathcal{N}(\cdot, \cdot)$ denotes the Gaussian distribution with standard deviation $\sigma$. We use the same fixed $\sigma$ for all pixels and perform background subtraction by means of the following binary hypothesis test applied to $P_B(\cdot)$:

$$P_B(T_n[x]) \begin{cases} B \\ F \end{cases} \geq \eta$$ (3)

where $\eta$ is a fixed threshold, identical for all pixels. We refer to this overall background subtraction model as Running Gaussian Average based Background Subtraction (RGA BS) and show a sample result in Fig. 3b.

The background subtraction model discussed so far uses temporal information to separate the foreground from the background. However, all decisions are made independently at neighboring pixels, thus leading to fragmented body-temperature areas. In order to address this, one needs to leverage the spatial contiguity of the human body by applying spatial constraints to foreground estimates. For this purpose, we use an approach proposed by McHugh et al. [7]. They used a Markov Random Field (MRF) model to ensure spatial estimate coherence within a binary hypothesis test as follows:

$$P_B(T_n[x]) \begin{cases} B \\ F \end{cases} \geq \eta \exp \left( \frac{Q_F[x] - Q_B[x]}{\gamma} \right),$$ (4)

where $P_F(T_n[x])$ is the probability that $T_n[x]$ belongs to the foreground, $Q_F[x]$ and $Q_B[x]$ denote the number of neighboring foreground and background pixels around location $x$, respectively, while $\theta$ and $\gamma$ are parameters. Unlike $P_B(\cdot)$, we assume $P_F(\cdot)$ is a constant (uniform distribution) because we observed that the foreground (body) temperature footprint characteristics can vary significantly depending on clothing, hairstyle and height of a person. Effectively, the right-hand side of the binary hypothesis test (4) is a spatially-adaptive threshold. Depending on the labels of neighboring pixels, the threshold will change. If there are more foreground pixels than background pixels in the neighborhood of $x$, the threshold will increase, and, therefore, it will be more likely that the pixel is deemed as belonging to the foreground (and vice versa). Due to the variable threshold, the MRF model increases spatial coherence of foreground estimates, which can be seen in Fig. 3c. The parameter $\gamma$ can be used to adjust the degree to which the MRF model impacts the threshold.

### 3.2. Event Detection

We propose two different event detection algorithms. Our baseline algorithm assumes that no more than one person will pass under a door at a given time. Our multi-person algorithm, however, is designed to handle multiple people simultaneously passing through the door.

#### 3.2.1 Baseline Algorithm

We define an event as a sequence of consecutive frames that satisfy the following conditions: (1) the frames immediately preceding and following the event are empty, i.e., have no foreground pixels, (2) each frame in the event has at least one foreground pixel, and (3) there is at least one frame in the event with at least $K$ foreground pixels, were $K$ is a
parameter which can be adjusted to account for the height at which the sensor is mounted above the door (smaller $K$ for greater heights).

(a) 32×24-pixel frame with two people passing through a door.

(b) Result of background subtraction using RGA+MRF BS algorithm with centroid (green star) computed using the baseline algorithm.

(c) Result of background subtraction using RGA+MRF BS algorithm with two centroids (red and blue stars) computed using the multi-person algorithm.

Figure 4: Thermal frame and results of background subtraction and centroid calculation for 2 people passing through a door.

3.2.2 Multi-Person Algorithm

In the baseline algorithm, we assumed that only one person passes under the sensor at a time. If multiple people pass through the door within the same event, the algorithm is incapable of distinguishing them (it calculates only one centroid), thus resulting in an error (Fig. 4).

To address this, we detect blobs among foreground pixels in each frame and track their movement. A blob is defined as a connected component of foreground pixels of size $L$ or more. We also define a blob track as a time sequence of blobs, one in each frame, that are linked between consecutive frames via association described below. We consider each blob track to be an event. Blob tracks start, grow and end as described below.

Blob track birth: If there are more blobs in the current frame than in the previous frame, a new blob track is created. The decision as to which blob will be associated with the new blob track is determined after data association in the growth phase.

Blob track growth: If the number of blobs in the current and previous frames is the same, then a one-to-one mapping is established between blobs in those frames thus leading to track growth. The track to which a previous-frame blob belongs is grown by a current-frame blob with which the previous-frame blob is associated. This association is established based on the Euclidean distance between blobs’ centroids. First, for each blob in the current frame the closest blob is found in the previous frame. Then, the blob pair with the smallest centroid-to-centroid distance is said to be associated with each other and removed from further consideration. The procedure is repeated for the remaining current-frame blobs. Other blob association methods could be applied as well, e.g., minimization of the sum of distances for all blob pairs. However, sophisticated methods may not work as well in our application context due to low thermal sensor resolution, short duration of events and the similarity of thermal footprints of different people.

Blob track termination: If there are fewer blobs in the current frame than in the previous frame, a blob track is terminated. The decision as to which blob is to be terminated is determined after data association in the growth phase.

3.3. Event Classification

Both algorithms classify each event at its completion into one of the following classes: (1) a person left the room or (2) a person entered the room. This is accomplished by analyzing the direction of movement of foreground pixels throughout the event. Let $F_n$ be defined as follows:

- baseline algorithm: a set of all foreground pixels at time $n$,
- multi-person algorithm: a set of all pixels belonging to a single blob at time $n$ (part of a blob track).

We compute the centroid $C_n$ at time $n$ as follows:

$$C_n = \frac{1}{|F_n|} \sum_{x \in F_n} x.$$

Since columns of a thermal frame are orthogonal to the door opening (Fig. 3a), we use the vertical component $C_n^v$ of centroid $C_n = [C_n^h, C_n^v]$ to determine whether a person enters
or leaves the room. In particular, we examine whether or not
the centroid crosses the mid-line of the frame between two
consecutive time instants \( n - 1 \) and \( n \). If \( C_n \) belongs to the
upper part of the frame (top 32 \( \times \) 12 pixels of the Melexis
32 \( \times \) 24 pixel sensor) whereas \( C_{n-1} \) belongs to the lower
part of the frame (bottom 32 \( \times \) 12 pixels) we predict that
the person is entering the room. Conversely, if \( C_n \) belongs
to the lower part of the frame whereas \( C_{n-1} \) belongs to its
upper part, we predict that the person is leaving the room.
Based on this decision, the people count is updated.

During a hesitant entry/exit or in case of lingering, an
event might involve multiple mid-line crossings. We ex-
amine the first and last crossings within an event. If the
directions of these two crossings are the same, we decide as
described above. If the directions differ, we consider this to
be a case of lingering and do not update the people count.

4. Experimental Results

4.1. Dataset

We collected a dataset of thermal image sequences using
two Melexis MLX90640 32 \( \times \) 24-pixel sensors running at 16
Hz mounted above two doors (Fig. 1) of a small classroom.
Compared to previous research \cite{2}, \cite{12} our sensor has a
slightly higher spatial resolution, but still a person cannot
be visually recognized from the captured data (Figs. 3a, 4a).

Our dataset, called TIDOS (Thermal Images for Door-
based Occupancy Sensing), is publicly available\footnote{vip.bu.edu/tidos} and
includes several types of door activity: single person enter-
ing/leaving the classroom, multiple people entering/leaving
through the same door, people lingering in the door, people
with backpacks, in thick clothing, carrying various items,
etc. Details of the dataset are provided in Table 1. We
manually annotated each frame in the dataset with a number
which equals the change in the people count (if any). Such a
change can only occur at the end of an event. During anno-
tation, an event is considered to have ended when a person
completely leaves the frame. We computed the ground-truth
people count in the room using our annotations and the ini-
tial people count in the room (Table 1).

4.2. Performance Analysis

We evaluated the performance of our algorithms on TI-
DOS using the following algorithm parameters: \( \alpha = 0.05 \)
\( \sigma = 0.4 \) and \( \eta = 0.015 \) in the RGA model, \( \theta P_F(T_n[x]) = 0.015 \) (a constant for all \( x \)) and \( \gamma = 0.2 \) in the MRF-based
hypothesis test, and blob-size threshold of \( K = L = 100 \)
for both baseline and multi-person algorithms. The values of
\( \alpha, \sigma, \eta, \gamma, \theta P_F \) were selected heuristically. However, the
values of \( K \) and \( L \) are motivated by the typical size of a
human body’s projected image onto the sensor. Based on
physical constraints of our setup (55\( ^\circ \) \( \times \) 35\( ^\circ \) sensor FOV,
2.4m installation height, 1.7m average human height), we
concluded that a body’s projection typically occupies 200–
250 pixels and this agrees with our observation of recorded
data. We used 100 as our threshold to avoid misses in case
of shorter people, especially children.

Since both algorithms estimate transitions in the state of
a room (people-count changes), in order to estimate the state
of the room (people count) an initial state of the room is
needed. In our experiments, we used the true initial people
count in each room reported in Table 1.

We use three metrics to evaluate the performance of our
algorithms. The first two metrics assess the raw people-
count estimation performance and are based on Mean Ab-
solute Error (\( MAE \)). Our third metric addresses the drift
problem, that leads to error accumulation, and temporal
misalignments between ground-truth and estimated people-
count changes.

4.2.1 Basic Metrics for Count Estimation

Our basic performance metric is the \( MAE \) between the true
and estimated people counts averaged across all \( N \) frames
of a thermal sequence. The value of \( MAE \) is unaffected
by the initial count. However, it scales with the number of
people entering/leaving a room which confounds the com-
parison of \( MAE \) values across different occupancy-density
scenarios. Thus, we propose another evaluation metric
which accounts for the number of people in a room, namely
the Per-Person Mean Absolute Error \( MAE_{PP} \), defined as fol-
loows:

\[
MAE_{PP} = \frac{1}{N} \sum_{n=1}^{N} \left| \hat{y}_n - y_n \right|
\]

where \( y_n \) and \( \hat{y}_n \) are the ground truth and estimate of the
number of people in a room at time \( n \), respectively, and \( N \) is
the total number of frames in the recording. While, in prin-
ciple, the denominator in \( (5) \) could be zero, recordings with
no people entering/leaving a room are not interesting for al-
gorithm assessment and are absent from our dataset. We
show the performance of our algorithms in terms of \( MAE \)
and \( MAE_{PP} \) in Table 2 and in terms of frame-wise peo-
dle count in Fig. 5. Unlike \( MAE \), the value of \( MAE_{PP} \) is
influenced by the initial state of the room since that affects
the denominator of Eq. \( (5) \). Moreover, for all recordings
in TIDOS, the denominator of Eq. \( (5) \) is larger than \( N \), the
number of frames in a recording. This causes the \( MAE_{PP} \)
value to be consistently smaller than the \( MAE \) value for
the same algorithm applied to the same video.

**Baseline algorithm:** The baseline algorithm has high
\( MAE \) and \( MAE_{PP} \) values for “Lunch Meeting 1”, “Lunch
Meeting 3”, “Edge Cases” and “High Activity” recordings.
This is due to multiple-person events that the algorithm
Table 1: Details of TIDOS (Thermal Images for Door-based Occupancy Sensing) dataset. Each 32×24-pixel frame was acquired by Melexis MLX90640 sensor at 16 fps. Data was collected by 2 sensors, one over each door of a small classroom.

| Thermal Recording      | Number of frames | Number of entries and exits | Initial people count | Challenges (scenario)                                                      |
|------------------------|------------------|-----------------------------|----------------------|--------------------------------------------------------------------------|
| Lecture                | 7,520            | 2                           | 9                    | Lingering in doorway (only single-person events)                          |
| Lunch Meeting 1        | 37,536           | 25                          | 0                    | Wearing a coat; carrying various items; multiple people passing through at the same time |
| Lunch Meeting 2        | 9,344            | 8                           | 12                   | Carrying a backpack (only single-person events)                           |
| Lunch Meeting 3        | 28,128           | 69                          | 7                    | Lingering in doorway; wearing a hoodie or carrying a backpack; two people standing in a door and handshaking; multiple people passing through at the same time |
| Edge Cases             | 13,120           | 24                          | 6                    | Long lingering in doorway; one or two people standing in a door while another person is passing through; multiple people passing through at the same time |
| High Activity          | 22,560           | 133                         | 4                    | Wearing a hoodie or thick coat; carrying a backpack; pushing a chair through doorway; leaning against a closed door; one person standing in a door while another one is passing through; multiple people passing through at the same time |

Table 2: Performance comparison of the proposed algorithms on TIDOS dataset using three metrics. The lowest values for MAE and MAE<sub>PP</sub> and the highest value for CCR<sub>WCC</sub> for each recording are shown in boldface.

|                      | Baseline algorithm | Multi-person algorithm |
|----------------------|--------------------|------------------------|
|                      | MAE    | MAE<sub>PP</sub> | CCR<sub>WCC</sub> | MAE     | MAE<sub>PP</sub> | CCR<sub>WCC</sub> |
| Lecture              | 0.392  | 0.043   | 0.500             | **0.003** | **0.001**   | **1**               |
| Lunch Meeting 1      | 0.812  | 0.167   | 0.880             | **0.319** | **0.065**   | **0.888**           |
| Lunch Meeting 2      | **0.009** | **0.001** | **0.777**         | 0.016    | **0.001**   | **0.777**           |
| Lunch Meeting 3      | 0.973  | 0.137   | 0.826             | **0.052** | **0.007**   | **0.905**           |
| Edge Cases           | 0.868  | 0.166   | 0.666             | **0.548** | **0.105**   | **0.807**           |
| High Activity        | 1.431  | 0.239   | 0.651             | **0.945** | **0.158**   | **0.753**           |

cannot handle. As expected, the algorithm works well for single-person events as confirmed by low error values for “Lecture” and “Lunch Meeting 2” recordings.

**Multi-person algorithm:** The multi-person algorithm performs very well on “Lecture” and “Lunch Meeting 2” confirming its ability to handle single-person events. It also performs well on “Lunch Meeting 1”, “Lunch Meeting 3” and “Edge Cases” recordings that contain multiple-person events. Admittedly, it mishandled one of the multi-person events in “Lunch Meeting 1” (Fig. 5b, around frame 18,000). The multi-person algorithm does not perform as well on “High Activity”, as it is the most challenging recording in the dataset (see Table 1). Not only does “High Activity” contain the largest number of events, its range of challenges is also widest. Overall, however, the multiperson algorithm significantly outperforms the baseline algorithm in both MAE and MAE<sub>PP</sub> on all thermal recordings except for “Lunch Meeting 2” for which the error is extremely small anyway.

This performance improvement can be also seen in frame-wise people-count plots (Fig. 5). While the baseline algorithm suffers from count drift due to mishandling multiple-person entries/exits (latter parts of “Lunch Meeting 1” and “Lunch Meeting 3”), the multi-person algorithm handles these cases correctly. Clearly, both algorithms have some difficulty with the challenging “High Activity” recording but the multi-person algorithm tracks the ground truth more accurately than the baseline algorithm, which is reflected in MAE and MAE<sub>PP</sub> values.

4.2.2 Metric Robust to Temporal Misalignments and Error Accumulation

Despite a very accurate estimate of counts by both algorithms in “Lunch Meeting 2” (Fig. 5), their MAE and MAE<sub>PP</sub> values are not zero. This is due to the fact that although all events have been correctly classified, the timings of a ground-truth event (marked at its completion) and
Figure 5: True (blue) and estimated (red) people-count plots for the proposed algorithms across all recordings in the TIDOS dataset. To distinguish between the red and blue curves in frames where their values exactly coincide, we added a positive vertical offset of 0.1 person to the blue curves. Note that since at each time instant two frames are collected (one by each door sensor), the number of frames in these plots is one-half of the total number of frames in Table 1.

of its estimate may slightly differ. For instance, in the event definition of the multi-person algorithm, a person is considered as “leaving” a frame if the associated blob has less than $L$ pixels. However, during our manual annotation a person was considered as out of the frame if s/he left the frame completely. These slight temporal misalignments contribute non-zero values to $MAE$ and $MAE_{PP}$ for a few frames. We can ignore the effects of small temporal misalignments during performance assessment by examining whether the estimated count change occurs within a small temporal window $w$ around the time that the true count change takes place.

Furthermore, $MAE$ and $MAE_{PP}$ apply to people counts and are sensitive to error accumulation because a
single miscount could potentially contribute an MAE of 1.0 irrespective of the recording duration N. Clearly, a new evaluation metric, resistant to cumulative errors, is needed. Such a metric should focus on changes in people counts rather than the counts themselves.

Motivated by these dual considerations, we introduce a new metric, Windowed Count-Change (WCC) Correct Classification Rate (CCRWCC), that accounts for both temporal misalignments and error accumulation, and is defined as follows:

\[
\begin{align*}
    e_n &= \min_{-w \leq \delta \leq w} |(y_{n+1} - y_n) - (\hat{y}_{n+1} + \delta - \hat{y}_n + \delta)| \\
    \delta_n &= \arg \min_{-w \leq \delta \leq w} |(y_{n+1} - y_n) - (\hat{y}_{n+1} + \delta - \hat{y}_n + \delta)| \\
    \tilde{N} &= \bigcup_{m=1}^{N-1} \{m + \delta_m\}, \\
    CCR_{WCC} &= \frac{|\{n : (y_{n+1} \neq y_n) \land (e_n = 0)\}|}{|\{n : (y_{n+1} \neq y_n) \lor (e_n \neq 0)\}| + M} \\
    M &= |\{n \notin \tilde{N} : \hat{y}_{n+1} \neq \hat{y}_n\}|
\end{align*}
\]

This metric measures the fraction of frames having count changes in which the estimated count-change equals the true count-change within ±w frames. However, it ignores the frames for which both the estimated and true changes are zero (no door event) which occur very frequently and would skew the traditional definition of CCR. CCRWCC is not only resistant to cumulative errors, but also to jitter: even if a prediction is delayed by ±w frames compared to ground truth, it can still be considered as correct. This metric is essential for applications where misses and false positives need to be minimized, for example monitoring of entryways to a high-security area. A more detailed explanation of CCRWCC can be found on our website.\(^3\)

However, w needs to be judiciously selected; a large w would unjustly boost CCRWCC. We have considered two constraints on w, a physically-motivated one and a statistically-motivated one. Given our door setup (sensor’s 55° × 35° FOV and 2.4m installation height) and a typical speed of 1.2 m/sec for a person entering/exiting a room, we concluded that this person will be at least partially captured in thermal frames for about 1.3 sec. Therefore, w should be less than 1.3 sec in order to ensure that the person immediately following would not be considered as a potential match within ±w. We have also computed a histogram of time differences between estimated and ground-truth entry/exit times for all events in TIDOS. Over 90% of these time differences were within 1 sec. Consequently, in all experiments we used w = 16 frames (1 sec).

The results of Table 2 show that both algorithms fare equally well in terms of CCRWCC on “Lunch Meeting 1” and “Lunch Meeting 2”, but the multi-person algorithm clearly outperforms the baseline algorithm by a significant margin on all other recordings. It is also interesting to note that small MAE and MAEPP values need not imply a higher CCRWCC value. Both baseline and multi-person algorithms have lower MAE and MAEPP values for “Lunch Meeting 2” than for “Lunch Meeting 1”, yet their CCRWCC values for “Lunch Meeting 1” are much higher than for “Lunch Meeting 2”. This phenomenon may be partially attributed to the fact that in evaluation metrics such as MAE and MAEPP, two errors that occur in opposite directions could cancel out each other. For example, if an algorithm misclassifies one entry event and later misclassifies one exit event, the people count errors due to these two misclassifications will “cancel” each other out resulting in zero count errors beyond the second event.

It is clear from Table 2, that on “High Activity” the multi-person algorithm outperforms the baseline algorithm by a margin of 0.102 in terms of CCRWCC value. This is a significant improvement because the “High Activity” recording has the highest number of entry and exit events and, therefore, a 0.102 fraction of events corresponds to around 13 entries/exits. Moreover, CCRWCC of 0.753 suggests that three out of four entries and exists were correctly detected and classified within 1 sec of their true occurrence. This is a very solid classification rate for a recording that is mostly composed of very challenging entry/exit scenarios (see Table 1).

5. Conclusions

In this work, we developed and systematically studied an overhead virtual tripwire configuration for people counting using a low-resolution thermal sensor. We believe this is the first comprehensive study of its kind encompassing sensor system design and deployment, dataset collection and annotation, algorithm development, design of new performance metrics, and performance evaluation of developed algorithms. The achieved results indicate that typically 80-90% entry and exit events are correctly classified for scenarios with a wide range of extreme challenges, while in simpler, less-active scenarios even 100% correct classification can be reached. We hope that this work and the new publicly-available dataset will stimulate further research.

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