Abstract—Timely recognition of threats can be significantly supported by security assistance systems that work continuously in time and call the security personnel in case of anomalies. We are describing the concept and the realization of an indoor security assistance system for real-time decision support. Data for the classification of persons are provided by chemical sensors detecting hazardous materials. Due to their limited spatio-temporal resolution, a single chemical sensor cannot localize this material and assign it to a person. We compensate for this deficiency by fusing the output of multiple, distributed chemical sensors with kinematical data from laser-range scanners. Both tracking and fusion of tracks with chemical attributes can be processed within one framework called Probabilistic Multiple Hypothesis Tracking (PMHT). An extension of PMHT for dealing with classification measurements (PMHT-c) already exists. We show how PMHT-c can be applied to assign chemical attributes to person tracks. This affords the localization of threads and a timely notification of the security personnel.

Keywords: Person Tracking, Probabilistic Multiple Hypothesis Tracking (PMHT), Classification, Attributes, Data Fusion, Security Assistance Systems

I. INTRODUCTION

Freedom of movement for people as well as freedom to come together safely in open public events or utilities is vital for each citizen. The defence of this freedom against ubiquitous threats requires the development of intelligent security assistance systems that comprise state-of-the-art surveillance technology and work continuously in time. In our work we demonstrate core functions of an indoor security assistance system for real-time decision support that is based on a heterogeneous sensor suite and multiple sensor fusion techniques. Within this system, potential threats are classified, tracked and localized in order to focus the attention of the security personnel.

Basic input data for the classification are provided by chemical sensors detecting hazardous materials, such as explosives. However, due to the fact that these sensors have a limited spatio-temporal resolution, an individual chemical sensor is unable to localize hazardous material and assign it to potentially threatening persons in the surveillance area. Our system realizes an integrative approach that compensates this deficiency in dynamic scenarios by fusing the output of several chemical sensors with kinematical data from laser-range scanners used for multiple person tracking (fig. 1).

The incoming laser measurements can be assigned to the constructed and successively updated tracks in many ways. Therefore the solution of the assignment problem is the central task of every multiple target tracking algorithm. The traditional approaches to multiple hypothesis tracking rely on the complete enumeration of all possible interpretations of a series of measurements and avoid an exponential growth of the arising hypothesis trees by various approximations (MHT: Multiple Hypothesis Tracking [2], [3], (J)PDAF: (Joint) Probabilistic Data Association Filter [1]). A powerful, alternative approach is represented by the Probabilistic Multiple Hypothesis Tracking (PMHT) [7], [8], [10], [11], [14]. Essentially, PMHT is based on Expectation-Maximization (EM) for handling assignment conflicts. It works on a sliding data window and exploits the information of previous and following scans in every of its kinematic state estimates [5], [9]. Linearity in the number of targets and measurements is the main motivation for a further development and extension of this methodology.

The original formulation of PMHT [7], [8] deals with measurements that are instantaneous observations of the state of a particular model – here, the kinematical model of a person. The problem of assigning measurements to targets arises because the particular model that caused a measurement is unknown. Thus PMHT forms an estimate of the unknown model states based on the state observation with uncertain origin. In practical applications, a sensor may be able to obtain other information besides the state observations. [4] considers the case where the tracking filter has an estimate of the class of the target that caused each available state observation and extended the PMHT for dealing with classification mea-
measurements (PMHT-c). A classification measurement is treated as an observation of the assignment of the corresponding measurement. One example for such a measurement is the range profile that occurs in high resolution radar. However, in our security scenario there is no fixed association between a position measurement and a chemical output. We show how PMHT-c can nevertheless be applied and used to estimate the alert levels of the persons in the surveillance area.

The remainder of this work is organized as follows: Section II provides our notations. Section III deals with the incorporation of classification information into the PMHT framework. In section IV we show experimental results. And in section V we summarize and describe the future work.

II. NOTATIONS AND FUNDAMENTALS

Let $S$ be the number of persons that are moving in the surveillance area and that are observed by multiple laser-range scanners. The sensors generate a measurement series $Z = Z_{1:T} = \{z_t, N_t\}_{t=1}^T$ for a time interval $[1 : T]^3$. The sensor output at a scan $t$ not only consists of the set of measurements $z_t$ but also of the number of measurements $N_t$. Measurements $z_t^n \in \mathbb{R}^2$ with $n \in [1 : N_t]$ are assumed to be Cartesian position data. The task of person tracking consists in estimating the kinematic states $X = X_{1:T} = \{(x_t^n)_{s=1}^S\}_{t=1}^T$ of the observed persons. The states $x_t^n \in \mathbb{R}^3$ with $s \in [1 : S]$ comprise position and velocity. Each person moves according to the discrete-linear model in eq. (1) and (2)

\[
x_t^{n+1} = F x_t^n + v_t^n \tag{1}
\]

\[
y_t^{n} = H x_t^n + w_t^n \tag{2}
\]

with random sequences $\{v_t^n, w_t^n\}$ that are assumed to be white, zero-mean, Gaussian, and mutually independent, with $E\{v_t^n, v_t^{n'}\} = Q$ and $E\{w_t^n, w_t^{n'}\} = R$ vs. $t$. $F$ is the state transition matrix and $H$ is the observation matrix. Difficulties arise from unknown assignments $A = A_{1:T} = \{a_t^n\}_{t=1}^T$ of measurements to persons. The assignments are modeled as random variables $a_t^n = \{a_t^n\}_{t=1}^{N_t}$ that map each measurement $n \in [1 : N_t]$ to one of the persons $s \in [1 : S]$ by assigning $a_t^n = s$. Expression (2) is the observation. Hence, it is

\[
z_t^n = y_t^{a_t^n}. \tag{3}
\]

Mathematically expressed, the optimization problem

\[
\arg \max_N p(X|Z) \tag{4}
\]

is to be solved and PMHT is an efficient method for this task. It works on a sliding data window (also called batch), and exploits the information of previous and following scans in each of its kinematic state estimates. For each window position, PMHT applies the method of Expectation-Maximization (EM) [5], [9] to the underlying data. EM is an iterative method for localizing posterior modes.

At each iteration, EM first calculates posterior weights $p(A|Z, X^l)$. The posterior weights define an optimal lower bound

\[
Q(A; X^l) = \log p(X^l) + \sum_A \log(p(A, Z|X^l)) p(A|Z, X^l) \tag{5}
\]

of $p(X|Z)$ at the current guess $X^l$, whereas $l$ is the iteration index. Since $Q(A; X^l)$ is expressed as an expectation, this first step is called Expectation-Step (E-Step). In the following Maximization-Step (M-Step), EM maximizes the bound with respect to the free variable $X^l$, which leads to improved estimates $X^{l+1}$. The new estimates control the lower bound of the following E-Step. E-Step and M-Step are repeated until the estimates converge. How the M-Step is done depends of course on the application. PMHT is the application of EM to the tracking problem. It results in estimates $x_t^n$ for each target $s \in [1 : S]$ at each time $t \in [1 : T]$. Covariance matrices $P_t^n$ occur as a by-product. They cannot be proven to be the error covariance matrices of the point estimates $x_t^n$, but nevertheless have a useful role.

III. PMHT WITH CHEMICAL CLASSIFICATION

The basic PMHT has been extended for dealing with classification measurements by Davey [4] who calls this extension PMHT-c. In this section we describe how the PMHT-c algorithm can be applied within our security assistance system. The core of this algorithm is a standard PMHT (III-A). The extensions corresponding to [4] enable PMHT to estimate classifications (III-B).

A. Multiple Person Tracking

Using the language of EM, the unknown associations $A$ of measurements to targets are the so-called Hidden Variables. For certain associations $A$, measurements $Z$ and kinematic state estimates $X$ we obtain

\[
p(Z, X, A) = \prod_{s=1}^S p(x_t^s) \prod_{t=2}^T \prod_{s=1}^S p(x_t^s | x_{t-1}^s) 
\]

\[
\times \prod_{t=1}^T \prod_{n=1}^{N_t} \pi_{n \rightarrow a_t^n} N(z_t^n; H x_t^{a_t^n}, R_t^{a_t^n}), \tag{6}
\]

whereas the expression $N(y; \mu, \Sigma)$ denotes the multivariate Gaussian density with random variable $y$, expected value $\mu$ and covariance $\Sigma$. $\pi_{n \rightarrow \cdot}^{a_t^n}$ is the prior probability $p(a_t^n = s)$. Starting from (6) the following algorithm can be derived [7]:

1) Expectation-Step (E-Step): Calculate the posterior assignment probabilities that a measurement $n$ at scan $t$ refers to person $s$ according to formula (7).

\[
w_t^{n \rightarrow a_t^n}(l) = \frac{\pi_{n \rightarrow a_t^n}^{a_t^n}(l) N(z_t^n; H x_t^{a_t^n}(l), R_t^{a_t^n})}{\sum_{s'=1}^S \pi_{n \rightarrow a_t^{s'}}^{a_t^{s'}}(l) N(z_t^n; H x_t^{a_t^{s'}}(l), R_t^{a_t^{s'}})} \tag{7}
\]

The weights are calculated for all scans $t$ of the current window position and for all measurements with respect to all persons. They are based on the measurements $z_t^n$ and the current state estimates $x_t^n(l)$. Obviously the weights comprise
two kinds of measures that evaluate the relevance of a measurement with respect to a person estimate: A distance measure which is given by the Gaussian \( N(z_t^s; Hx_t^s(l), R) \) and a “visibility measure” which is given by \( \pi_t^{n-s} := p(a_t^n = s) \). The latter reflects how likely it is to detect a person not taking the concrete distance of a measurement to the person’s position into account. In a radar scenario, these probabilities are governed by the sensor parameters and target properties: false measurement density, number of false measurements and detection probability. There exist formulae to calculate this “visibility measure” at each scan [10]. In our security scenario, the visibility of a person is only influenced by the degree of occlusion. In case of no occlusion, a person surely has a detection probability of 100%, in case of full occlusion of occlusion. In case of no occlusion, a person surely has a detection probability of 100%, in case of full occlusion the detection probability is 0%. The degree of occlusion of a person is reflected by the number of laser beams that hit the person. So the \( \pi_s \) can be easily estimated taking the number of measurements \( N_t \) and the weights \( w_t^{n-s}(l) \) into account. This corresponds to the standard PMHT update formula (8) as developed by Streit [7].

\[
\pi_t^{n-s}(l + 1) = \frac{1}{N_t} \sum_{n=1}^{N_t} w_t^{n-s}(l)
\]  

(8)

If there are almost no measurements in the neighborhood of the current estimate of a person, the sum of weights in eq. (8) and hence \( \pi_t^{n-s}(l + 1) \) is relatively small. If all persons are equally irradiated by the laser-range scanners then the \( \pi_s \)'s are uniformly distributed.

Subsequently, using the assignment weights in (7) we have to form synthetic measurements and corresponding covariances according to

\[
\bar{z}_t^s(l) = \frac{\sum_{n=1}^{N_t} w_t^{n-s}(l) z_t^n}{\sum_{n=1}^{N_t} w_t^{n-s}(l)}
\]

\[
\bar{R}_t^s(l) = \frac{R}{\sum_{n=1}^{N_t} w_t^{n-s}(l)}
\]

(9)

A synthetic measurement referring to a person \( s \) is the suitably weighted sum of all measurements reported at a certain scan \( t \). In the case of Cartesian Measurements, the measurement error covariance is constant (\( R \) for all measurements), which leads to centroid measurements with covariances \( \bar{R}_t^s(l) \) (9).

In general the error covariance of a measurement reflects its certainty, that is, to what degree we can trust the position information delivered by this measurement. Measurements with a small error are highly trusted during the data fusion process. In contrast, measurements with a significant error do not influence the estimation of a track. The synthetic error covariance \( \bar{R}_t^s(l) \) is a problematic issue of the basic PMHT algorithm. In a radar scenario, multiple false measurements in the neighborhood of the current track estimate could pretend to be one measurement of high accuracy: As the posterior weights of the E-Step are normalized with respect to the targets, the covariance denominator in (9) can be greater than unity and an accumulation of false measurements could lead the estimated track into a wrong direction. Note that

in a radar scenario tracked targets (targets of interest) are point targets and can produce at most one measurement per scan. The other measurements are false measurements. This effect is called Hospitality, and there are publications that discuss this problem in detail [10], [14]. However, in our person-tracking scenario, it is quite natural that multiple measurements belong to a person in the corridor. And we observed that this clustering behavior is in fact suitable in the context of track maintenance within a laser-range scanner sensor suite. Nevertheless, the following point should be mentioned: Figure 2 demonstrates that the laser measurements are not equally distributed over the border of a person’s body (here modeled as an ellipsoid). So the synthetic measurement marked as black cross does not lie in the center of the person, and the very small error covariance \( \bar{R}_t^s(l) \) pulls the estimate away from the person’s center towards the barycenter of the measurements. As a result we see a wiggly track although the person is walking along a straight line. We chose \( \bar{R}_t^s(l) \) as

\[
\bar{R}_t^s(l) := \begin{pmatrix} \frac{w}{2}^2 & 0 \\ 0 & \frac{w}{2}^2 \end{pmatrix}
\]

(10)

whereas \( w \) is the width of the person ellipsoid. Using this as a “synthetic” error covariance, leads to a smoother person track. A worsening in terms of track maintenance compared to standard PMHT could not be observed.

2) Maximization-Step: Each person track is updated by means of a Kalman Smoother that processes the synthetic values. This leads to new, improved state estimates \( x_{1:T}^s(l+1) \).

E-Step and M-Step are repeated until the state estimates do not considerably change anymore (convergence). After convergence, the prediction \( x_{1:T}^{n+1} \) is to be calculated for the following window position. When all persons have been processed, the window is shifted by one scan and the iteration process is started for the new window position.

B. Incorporating Classification Information

The PMHT algorithm derived in [4] was designed to take advantage of classification measurements to improve data association and state estimation. In the considered scenarios, the classification measurements could be utilized to improve tracking, because for each position measurement the corresponding classification output was known. The author uses the given assignment information between a kinematical state and
a classification and hence deals with pairs of measurements that consist of a kinematical and a classification observation. High resolution radar is mentioned as one example of a system where these classification measurements exist. Range profiles from various azimuth angles form a radar image of the target. The location of primary scatterers and other features can be used to classify the target.

In our security assistance system, the situation is different. There are classification measurements provided by the chemical sensors, but we do not have any information about their assignment to the laser measurements. To apply the cited PMHT extension we have to consider the scenario in a different way: In the security scenario there are also pairs of position information and classification output available, but the position information is not provided by a laser-range scanner.

In fact it is given by the chemical sensor placement and output. So referring to the experimental corridor in figure 3, we have five measurement pairs at each scan $t$. Each of them consists of the position information of the chemical sensor and its classification output.

In an early version of our algorithm [12], we used the installation place of each chemical sensor as its position information, which leads to the following effect: The closer a person is to a chemical sensor, the higher is the influence of the reported sensor output with respect to the classification of this person. This approach should be used if the mathematical model of the chemical sensor is unknown, and further information, e.g. about the approximative distance of the hazardous material, cannot be derived from the chemical output. The procedure fails if another person, not carrying an explosive, stays closer to the sensor than the dangerous one.

A precise mathematical model of a chemical sensor could yield more useful position information, e.g. an estimated distance of the chemical source based on the amplitude of the chemical signal. In this case the position measurement belonging to a certain classification output lies on a circle whose radius is determined by the value of the concentration amplitude. In other words, a low amplitude corresponds to a big radius (estimated distance from source to sensor) and a high amplitude implies a small radius tight around the sensor. Based on an accurately derived, precise model, the classification algorithm can be significantly improved.

The existence of the above described measurement pairs (position and classification) affords the derivation of the PMHT-c algorithm as presented by Davey [4]. In the following we explain how to assign the chemical outputs to person tracks applying PMHT-c and to find out who is carrying the hazardous material.

Let $p_{ch}^{ch}$ denote the position information of the chemical sensor with index $ch \in [1 : 5]$. This can be either be the sensor’s installation place, which is independent of $s$ and $t$, or a position on an estimated circle based on the signal amplitude. The latter situation is sketched in figure 7 and will be explained later in more detail. In this case, the position information is dependent on $t$ and the estimated position of the currently processed person $s$. However, for the sake of simplicity, we omit the indices $s$ and $t$ in the following explanations.

Each chemical sensor has an associated classification measurement at each scan $t$. We denote the classification measurement associated with $p_{ch}$ as $o_{ch}$ and let the total measurement vector be the collection of the position and its associated classification measurement

$$z_{t}^{ch} := \left( p_{ch}^{ch}, o_{ch} \right).$$

(11)

Assume that $ch \in [1 : 5]$ and $n \notin [1 : 5]$. We will not deal with laser measurements in this part of the paper. The classification measurement is a discrete variable. We assume that it can take a value from five different classes which are denoted by colors: green stands for No Alert and yellow, orange, red and dark red symbolize the alert levels from 1 up to 4 (from low to high, fig. 4). The problem we have to solve can be formalized as follows: given the estimated kinematic states $\mathcal{X}(l)$ of the $S$ persons, we want to estimate their classification. The desired information is provided by the probability mass function $p(o_{ch}^{ch} | a_{ch})$, which is the probability that the classification process will produce the class output $o_{ch}^{ch} = i$ when the observation was in fact caused by person $a_{ch}^{ch} = s$. The classification estimates can be represented by a matrix (fig. 5). The rows correspond to the possible classification outputs (fig. 4), and the columns correspond to the persons. Such a matrix is called a confusion matrix. We denote the confusion matrix as $C = \{ c_{is} \}$ with $c_{is} = \sum_{l=1}^{T} \sum_{ch=1}^{5} p(o_{ch}^{ch} = i | a_{ch}^{ch} = s)$. Since in our security...
scenario the entries of the confusion matrix are not known, they belong to the Hidden Variables of the system. Hence the EM auxiliary function (5) has to be extended to
\[ Q(\mathcal{X}, \Pi, C; \mathcal{X}(l), \Pi(l), C(l)). \] (12)
Like the kinematic estimates \( \mathcal{X} \) and \( \Pi \), the classification estimates \( C \) are iteratively updated for each window position. The estimation is based on all sensors and refers to all persons that are in the surveillance area at the current time. Hence there is one confusion matrix per window position. The final estimation result for the confusion matrix of the current window serves as an initialization of the confusion matrix of the following window.

The estimates of the confusion matrix entries are found by iteratively maximizing the \( Q \)-function. This leads to the algorithm called PMHT-c that has been derived in [4]. To get the PMHT-c, the Expectation-Step (E-Step) and the Maximization-Step (M-Step) of the basic PMHT have to be extended by the classification estimation. We explain the significant steps as they are applied for our purposes.

1) Calculate Assignment Weights (E-Step): First we have to calculate the posterior assignment probabilities \( u_{t}^{ch\rightarrow s} \). According to the derivation by Davey [4] we use the following update formula (13).
\[ u_{t}^{ch\rightarrow s} = \frac{\pi_{t}^{ch\rightarrow s} \cdot N(p^{ch}, Hx^{t}, Cov) \cdot c_{op_{s}^{t}}}{\sum_{s'=1}^{S} \pi_{t}^{ch\rightarrow s'} \cdot N(p^{ch}, Hx^{t}, Cov) \cdot c_{op_{s}^{t}}}. \] (13)
These posterior weights reflect the relevance of a chemical output for the classification of a person \( s \) in the surveillance area. Since all outputs have a priori the same relevance, we set \( \pi_{t}^{ch\rightarrow s} \) to a constant (\( \forall s, l \)) which makes them vanish. The posterior assignment weights are mainly governed by the Gaussian \( N(p^{ch}, Hx^{t}, Cov) \), which is a measure for the distance between the position information of the chemical sensor with index \( ch \) and the current track estimate of person \( s \). The position information can either be the installation place of the sensor (fig. 6) or an estimated position based on a mathematical model that yields a functional relation between the signal amplitude and the distance of a chemical source. Figure 7 provides an example for the latter case. We see two persons walking in the surveillance area. Person 2 carries the explosive. We consider the outputs of sensor 1 at scan 3 and 4. At scan 3 the sensor has an output of level dark red. From the mathematical sensor model, we know that the chemical source must be located somewhere on the dark red dashed circle or at least very close to this circle. Hence, for each person we calculate the point on the circle with the shortest distance to the person (denoted as small black circles). At scan 4 the sensor switches to level orange and our sensor model yields the orange dashed circle with the two marked positions, one for each person. Another person standing between the sensor and person 2 would be farther away from the orange circle and therefore would cause a lower assignment weight. This is the essential advantage compared to the usage of the sensor installation place as position information. The covariance matrix \( Cov \) in (13) reflects the uncertainty of the position information and has to be experimentally determined.

Furthermore, if the distance of a person to a chemical sensor is greater than the detection radius of the sensor, then the corresponding assignment weight is set to a constant close to zero (e.g. the smallest positive number). \( c_{op_{s}^{t}} \) is the current estimate of the confusion matrix entry that associates the output of sensor \( ch \) with person \( s \), that is, the probability that \( s \) caused a certain alarm (level IV, III, II, I or No Alert). The posterior weights \( u_{t}^{ch\rightarrow s} \) are calculated for each sensor \( ch \) and each person \( s \) at each scan of the current PMHT window.

2) Maximize the \( Q \)-Function (M-Step): During the M-Step our parameter estimates have to be updated. Besides the estimates \( \mathcal{X}(l) \) and \( \Pi(l) \) for tracking purposes, we have to update the entries of the confusion matrix. Following [4], this means processing formula (14).
\[ c_{is}(l+1) = \frac{\sum_{t=1}^{T} \sum_{ch=1}^{5} \delta(q_{i}^{ch} - i) \cdot u_{t}^{ch\rightarrow s}(l)}{\sum_{t=1}^{T} \sum_{ch=1}^{5} u_{t}^{ch\rightarrow s}(l)}. \] (14)
Since PMHT-c works on a sliding data window, not only the relevance weights of the current scan are available, but also the whole history of the time window can be taken into account and evaluated (fig. 8).

To update the classification entry for a certain alert level \( i \in \{\text{green, yellow, orange, red, dark red}\} \) all posterior weights of sensors that indicate this level must be summed up. The
weights have to be normalized with respect to the whole window. For example, to get the entry that associates level dark red with the person \(s\) in figure 8, we have to calculate

\[
C(\text{dark red}, s) = \frac{w^{1 \rightarrow s}_1 + w^{5 \rightarrow s}_4}{\sum_{t=1}^{T} \sum_{ch=1}^{5} w^{ch \rightarrow s}_t} \quad (15)
\]

3) Initialization: Since the EM/PMHT algorithm is a hill climbing approach, it can guarantee only local convergence. Hence one has to think about a proper initialization. We decided to proceed as follows: When a person enters the surveillance area (that is the detection area of the chemical sensor collection), we set the confusion matrix values to a uniform distribution with respect to the alert levels.

IV. EXPERIMENTAL RESULTS

This section deals with the application of the PMHT-c algorithm to both simulated and real data.

A. Simulations

We demonstrate the classification ability of the PMHT-c algorithm in the following simulated situation: Two persons are walking slightly staggered from the left entry to the right entry of the main corridor (fig. 9 and 10). The length of the PMHT window (batch) is set to 6 scans, and a constant number of 4 iterations is processed. A track is extracted when a person passes one of the entrance areas (light yellow). In our scenario, the two person tracks are extracted at the same time so that they have the same batch length at each scan. We calculate the sum of all alert probabilities, that is

\[
\sum_{\text{Alert}=1}^{IV} C_{\text{Alert}, s} \quad (16)
\]

for each person \(s\) and renormalize these sums with respect to the persons. This number is shown at the head of each person track. The upper left wall block contains the current confusion matrix. The dangerous person is marked by a dark gray rectangle. The chemical sensors react according to the Euclidian distance of the chemical source. The output is quantized and symbolized by different colors according to figure 4.

Since we are in a simulated world, the behavior of the five chemical sensors is well-understood and absolutely reliable. Therefore we have the ability to include a precise mathematical sensor model which provides a suitable source distance for every possible chemical output. In the
and the renormalized classification values. The figures 11 and 12 show the recorded values from the entering of the persons at scan 2 up to the finish of the classification procedure at scan 31. The dashed and solid black lines show the sum of all alert probabilities (eq. 16) and the corresponding renormalized value, respectively. In other words, the solid line corresponds to the numbers plotted at the head of the tracks in figure 9 and 10. The four colored dashed-dotted lines show the values of the alert entries in the confusion matrix, i.e. \( C(i, s) \) for each \( i \in \{ \text{yellow, orange, red, dark red} \} \) for the particular person \( s \).

Figure 11. Classification results in scenario I (lower person = hazardous)

Figure 12. Classification results in scenario II (upper person = hazardous)

However, this simulation reflects perfect conditions. It is an idealization of the reality, and finding a suitable model for the reaction of a real chemical sensor turned out to be very hard.

B. Real-Time System

The real-time demonstrator was used for both characterization of the chemical sensor response and demonstration of the classification concept. The corridor was designed as an aisle of a width of 1.89 m, bounded by low-emission press board and with a U-turn in the middle (fig. 13). We set up three laser-range scanners and five chemical sensors. An accurate plan and a more detailed description can be found in [13]. In our first experiments, we used metal oxide (MOx) sensors that detect hydrocarbons like fuels, alcohols or solvents [13].

After processing a multitude of tests, we were able to empirically analyze the reaction of the chemical sensors. Figure 14 shows the results in two 3-dimensional plots. The upper plot shows the signal of a chemical sensor (averaged over several test runs), when a person with alcohol passes it at five different distances. The vertical axis corresponds to the signal amplitude. The horizontal axes show the time when the amplitude value was reached and the (constant) distance between the person trajectory and the wall where the sensor was installed. To get the complete sensor model we made an area interpolation with cubic splines, which is shown in the lower plot. The plots clearly show the high delay of about 10 seconds which occurs at each of the distances. After integrating an air ventilation system that simultaneously sucks and blows a sufficient amount of analyte from its source (the person) towards the sensor system, we were able to reduce the average delay from 10 to approx. 6 seconds. However, both a reliable determination of the delay and the derivation of the source distance from a given signal amplitude became a hard problem in the real-time environment. We have to point out that the values in figure 14 are averaged and that they can vary from time to time in an unpredictable way which makes the correct classification very difficult. The diffusion of an analyte is influenced by a many physical quantities and a mathematical model that makes the sensor-delay and the
source-distance reliably computable could not be derived yet.

Nevertheless we were able to produce some good results when the persons were walking well separated. Figure 15 shows snapshots of a real-time scenario with two persons. The first one carried an open bottle of phenol. Beginning at the person’s entry we let the PMHT batch grow until their exit. Since differing batch lengths can wrongly influence the classification, we only note the non-normalized classification estimations of eq. 14. We processed only one classification iteration. The assignment weights were calculated according to figure 6. The chemical output was compared to the position estimates lying a constant number of scans in the past.

V. SUMMARY AND FUTURE WORK

We have shown how PMHT-c can be applied for the purpose of combined person tracking and classification in the context of a security assistance system. Our simulations show that the algorithm can achieve reliable classification results if it works on the basis of an accurate sensor model. The problem of handling differing batch lengths will still keep us busy but should be easily solved soon.

However, regarding our real-time environment, many more experiments are necessary to find a suitable model of the chemical reaction. In particular, air circulations caused by the movement of the persons will play an important role. All of this can be improved by better chemical sensors that will surely be developed in the chemical community. Finally our work aims to integrate chemical sensors that detect real explosives like TATP.

REFERENCES