Hazardous Material Localization and Person Tracking

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ABSTRACT

Timely recognition of threats can be significantly supported by security assistance systems that work continuously in time and call the attention of the security personnel in case of anomalies. We describe 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 associate it with a person. We compensate 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 single 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 associate chemical attributes to person tracks. This affords the localization of threads and a timely notification of the security personnel.

1.0 INTRODUCTION

Freedom of movement for people as well as freedom of coming 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 to associate it with the persons in the surveillance area. Our system realizes an integrative approach which 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 (figure 1).

The incoming laser measurements can be associated with the constructed and successively updated tracks in many ways. Therefore the solution of the association 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 association 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]).

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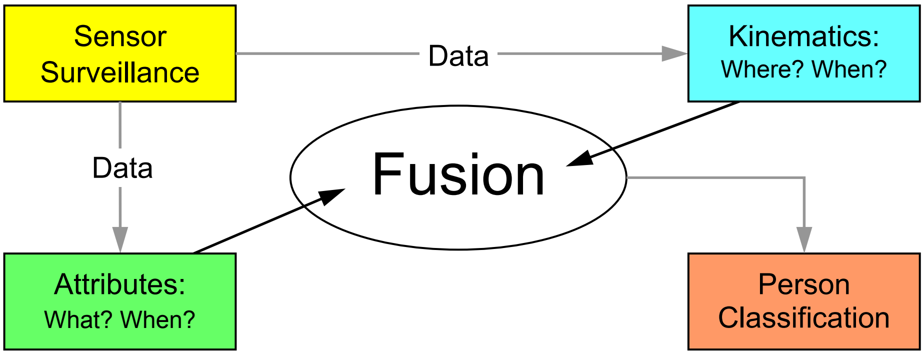


Figure 1: Fusion Concept

A powerful, alternative approach is represented by probabilistic multi-hypothesis tracking (PMHT) [6-8,10-12]. Essentially PMHT is based on expectation-maximization for handling with association conflicts. Linearity in the number of targets and measurements is the main motivation for a further development and extension of this methodology. PMHT has a characteristic property called *Hospitality*, which means that it welcomes multiple measurements as only one measurement with high accuracy. This property has already been analyzed in detail [10, 12] and turns out to be a problem referring to point target tracking. However, if one uses laser-range scanners to track persons it is a perfectly feasible event that one person generates multiple measurements and Hospitality should become an advantage. In section 3.1 we will take a closer look at this point.

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 associating 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 get other information besides the state observations. Davey [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 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 the position measurement and the chemical outputs. We show how PMHT-c can nevertheless be applied and be used to estimate the alert levels of the persons in the surveillance area. This affords the localization of threads and a timely notification of the security personnel.

2.0 NOTATIONS AND FUNDAMENTALS

The multiple person tracking scenario is defined as follows: 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 $\mathcal{Z} = \mathcal{Z}_{1:T} = \{\mathbf{z}_t, N_t\}_{t=1}^{T}$ for a time interval $[1:T]$[1]. The sensor output at a scan t not only consists of the set of measurements $\mathbf{z}_t$ but also of the number of measurements N_t. Measurements $\mathbf{z}_t^n \in \mathbb{R}^2$ with $n \in [1:N_t]$ are assumed to be Cartesian position data. The task of person tracking consists in estimating the kinematic states $\mathcal{X} = \mathcal{X}_{1:T} = \left\{\left\{\mathbf{x}_t^s\right\}_{s=1}^{S}\right\}_{t=1}^{T}$ of the observed persons (the person tracks). The states $\mathbf{x}_t^s \in \mathbb{R}^4$ with $s \in [1:S]$ comprise position and velocity.

Each person moves according to the discrete-linear model

[1] $[1:T]$ denotes the integral interval from 1 up to T

$$\mathbf{x}_{t+1}^{s} = \mathbf{F}\mathbf{x}_{t}^{s} + \mathbf{v}_{t}^{s} \tag{1}$$

$$\mathbf{y}_{t}^{a_t^n} = \mathbf{H}\mathbf{x}_{t}^{s} + \mathbf{w}_{t}^{s} \tag{2}$$

with random sequences $\{\mathbf{v}_t^s, \mathbf{w}_t^s\}$ that are assumed to be white, zero-mean, Gaussian, and mutually independent, with $\mathrm{E}\{\mathbf{v}_t^s \mathbf{v}_t^{s\top}\} =: \mathbf{Q}$ and $\mathrm{E}\{\mathbf{w}_t^s \mathbf{w}_t^{s\top}\} =: \mathbf{R}\ \forall \mathrm{s}, \mathrm{t}$. $\mathbf{F}$ is the evolution matrix and $\mathbf{H}$ is the measurement matrix. Difficulties arise from unknown associations $\mathcal{A} = \mathcal{A}_{1:T} = \{\mathbf{a}_t\}_{t=1}^{T}$ of measurements to persons. The associations are modelled as random variables $\mathbf{a}_t = \{a_t^n\}_{n=1}^{N_t}$ 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

$$\mathbf{z}_t^n = \mathbf{y}_t^{a_t^n}. \tag{3}$$

So mathematically expressed, the optimization problem

$$\arg\max_{\mathcal{X}} p(\mathcal{X}|\mathcal{Z}) \tag{4}$$

is to be solved. Probabilistic multi-hypothesis tracking (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 every 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. And a solution of the optimization problem (4) is found as follows:

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

$$\mathcal{Q}(\mathcal{X}; \mathcal{X}^l) = \log p(\mathcal{X}) + \sum_{\mathcal{A}} \log(p(\mathcal{A}, \mathcal{Z}|\mathcal{X}))\, p(\mathcal{A}|\mathcal{Z}, \mathcal{X}^l) \tag{5}$$

of $p(\mathcal{X}|\mathcal{Z})$ at the current guess $\mathcal{X}^l$ whereas l is the iteration index. As $\mathcal{Q}(\mathcal{X}; \mathcal{X}^l)$ 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 $\mathcal{X}$, which leads to improved estimates $\mathcal{X}^{(l+1)}$. The new estimates control the lower bound of the following E-Step. E-Step and M-Step are repeated until the estimates converge. The method converges to a local maximum of (4). 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 $\mathbf{x}_t^s$ for each person $s \in [1 : S]$ at each time $t \in [1 : T]$. Covariance matrices $\mathbf{P}_t^s$ occur as a by-product. They cannot be proven to be the error covariance matrices of the point estimates $\mathbf{x}_t^s$, but nevertheless have a useful role.

3.0 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 (3.1). The extensions corresponding to Davey [4] make PMHT able to estimate classifications (3.2).

3.1 Multiple Person Tracking

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

$$p(\mathcal{Z},\mathcal{X},\mathcal{A}) = \prod_{s=1}^{S} p(\mathbf{x}_1^s) \prod_{t=2}^{T}\prod_{s=1}^{S} \mathcal{N}(\mathbf{x}_t^s;\mathbf{F}\mathbf{x}_{t-1}^s,\mathbf{D}) \times \prod_{t=1}^{T}\prod_{n=1}^{N_t} \pi_t^{na_t^n} \mathcal{N}(\mathbf{z}_t^n;\mathbf{H}\mathbf{x}_{t|t-1}^{a_t^n},\mathbf{R}_t^n), \tag{6}$$

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

3.1.1 Expectation-Step (E-Step)

Calculate the posterior assignment probabilities that a measurement n at scan t refers to person s according to

$$w_t^{lns} = \frac{\pi_t^{ns}\mathcal{N}(\mathbf{z}_t^n;\mathbf{H}\mathbf{x}_t^{ls},\mathbf{R})}{\sum_{s'=1}^{S} \pi_t^{ns'}\mathcal{N}(\mathbf{z}_t^n;\mathbf{H}\mathbf{x}_t^{ls'},\mathbf{R})} . \tag{7}$$

The weights are calculated for all scans t of the current window position $\forall n, \forall s$. They are based on the measurements $\mathbf{z}_t^n$ and the current state estimates $\mathbf{x}_t^{ls}$. 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 $\mathcal{N}(\mathbf{z}_t^n;\mathbf{H}\mathbf{x}_t^{ls},\mathbf{R})$ and a "visibility measure" which is given by $\pi_t^{ns} := p(a_t^n = s)$. 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 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 π's can be easily estimated taking the number of measurements N_t and the weights w_t^{lns} into account. This corresponds to the standard PMHT update formulae (8) as developed by Streit [7].

$$\pi_t^{(l+1)ns} = \frac{1}{N_t}\sum_{n=1}^{N_t} w_t^{lns} . \tag{8}$$

If there are almost no measurements in the neighbourhood of the current estimate of a person, the sum of weight in (8) and hence $\pi_t^{(l+1)ns}$ is very small. If all persons are equally irradiated by the laser-range-scanners then the π's are uniformly distributed.

Hereupon, using the assignment weights in (7) one has to form synthetic measurements and corresponding covariances according to

$$\bar{\mathbf{z}}_t^{ls} = \frac{\sum_{n=1}^{N_t} w_t^{lns}\mathbf{z}_t^n}{\sum_{n=1}^{N_t} w_t^{lns}} \qquad \bar{\mathbf{R}}_t^{ls} = \frac{\mathbf{R}}{\sum_{n=1}^{N_t} w_t^{lns}} \tag{9}$$

A synthetic measurement referring to a person s is the weighted sum of all measurements that have been reported at a scan t. In case of Cartesian measurements the measurement error covariance is constant (denoted as $\mathbf{R}$ for all measurements) which leads to the centroid measurements and covariances in (9).

In general the error covariance of a measurement reflects its certainty, that is how strong we can trust in 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 big error do hardly influence the estimation of a track. The synthetic error covariance $\bar{\mathbf{R}}_t^{ls}$ is a problematic issue of the standard PMHT algorithm. In a radar scenario multiple false measurements in the neighbourhood of the current track estimates 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 a tracked target (target of interest) can produce at most one measurement at a scan. The other measurements are false measurements. This effect is called *Hospitality* and there are some publications that discuss this problem in detail [10, 12]. 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 behaviour is in fact suitable in the context of track maintenance within a laser-range-scanner sensor suite. Nevertheless, the following point is to be mentioned: Figure 2 demonstrates that the laser measurements are not equally distributed over the border of a person's body (here modelled as an ellipsoid).

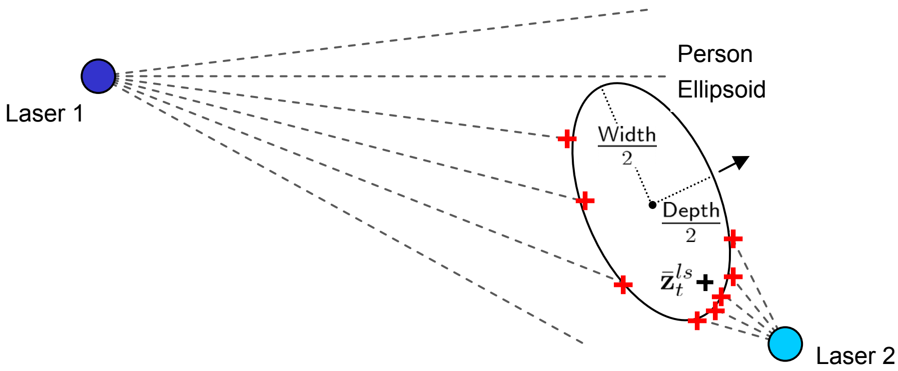


Figure 2: Person Scan of Laser-Range-Scanners

So the synthetic measurement marked as black cross does not lie in the centre of the person and the very small error covariance $\bar{\mathbf{R}}_t^{ls}$ pulls the current estimate away from the person's centre towards the barycentre of the measurements. As a result we see a wiggly track although the person is walking along a straight line. We chose $\bar{\mathbf{R}}_t^{ls}$ as

$$\bar{\mathbf{R}}_t^{ls} := \begin{pmatrix} \left(\frac{w}{2}\right)^2 & 0 \\ 0 & \left(\frac{w}{2}\right)^2 \end{pmatrix}, \tag{10}$$

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

3.1.2 Maximization-Step (M-Step)

The expectation-step of each iteration is followed by the maximization-step. In this step each person track is updated by means of a Kalman Smoother that processes the synthetic values. This leads to new, improved state estimates $\mathbf{x}_{1:T}^{(l+1)s}$. E-Step and M-Step are repeated until the state estimates do not considerably change anymore (convergence). After convergence, the prediction $\mathbf{x}_{T+1|T}^{s}$ is to be calculated for the following window position. When all persons have been processed, the data window is shifted by one scan and the iteration process is started again for the new window position.

3.2 Incorporating Classification Information

The PMHT algorithm derived by Davey [4] (PMHT-c) was designed to take advantage of classification measurements to improve data association and state estimation. In the considered scenarios of his work the classification measurements can be utilized to improve tracking, because for each position measurement the corresponding classification output is known. The author uses the given association information between a kinematical state observation 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 scatters 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 association to the laser measurements. To apply the cited PMHT extension we have to consider the scenario in a different way: Also in the security scenario there are *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. So referring to the experimental corridor in figure 3 we have five measurement pairs at each scan. Each of them consists of the chemical sensor position and its classification output.

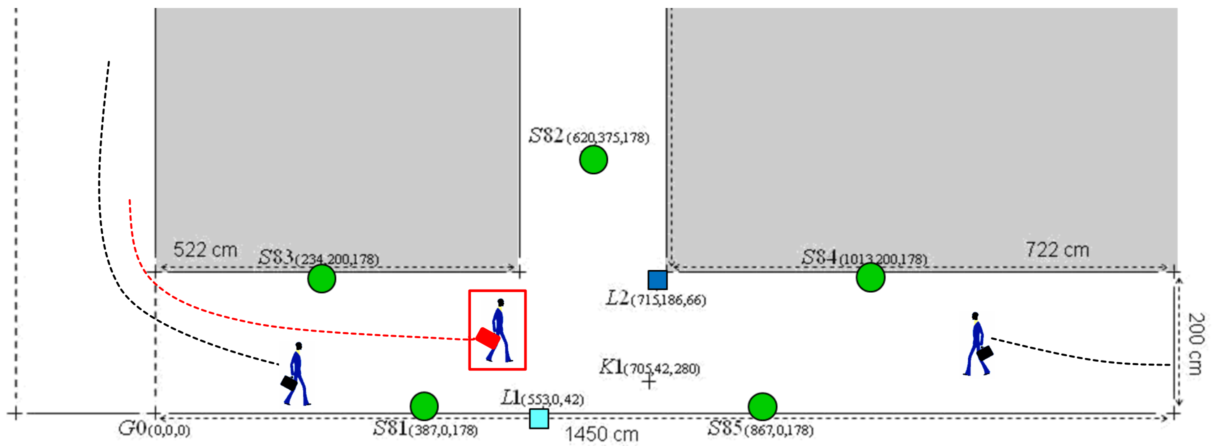


Figure 3: Experimental Corridor with five Chemical Sensors

The chemical sensors are symbolized as green filled circles. Furthermore there are two laser-range-scanners marked as cyan and blue filled rectangles. Exemplary we see three persons walking along the corridor, one of them carrying hazardous material in his bag. Now the question is how to associate the chemical attributes to the person tracks. In the following we explain how the PMHT-c algorithm can be applied to this problem.

Let $\mathbf{p}^{\mathsf{ch}}$ denote the position of the chemical sensor with index $\mathsf{ch} \in [1:5]$. As this position does not change we forgo the time index t. Each chemical sensor has an associated classification measurement at each scan t. We denote the classification measurement associated with $\mathbf{p}^{\mathsf{ch}}$ as o_t^{ch} and let the total measurement vector be the collection of the position (state observation) with its associated classification measurement.

$$\mathbf{z}_t^{\mathsf{ch}} \quad := \quad \begin{pmatrix} \mathbf{p}^{\mathsf{ch}} \\ o_t^{\mathsf{ch}} \end{pmatrix} \tag{11}$$

Assume that the laser-range-scanner measurements have indices that differ from any ch (that is $n \notin [1:5]$). We will not deal with them in this part. The classification measurement is a discrete variable that takes a value of an enumerated set of classes. The number of classes that define the possible classification values is usually not the same as the number of kinematical models. For example, the classes that arise due to poor resolution range profiles may be $\{\mathsf{small}, \mathsf{medium}, \mathsf{large}\}$. In our scenario we assume that the chemical classification can take a value from five different classes. We denote them by colours, whereas green stands for No Alert and yellow, orange, red and dark red symbolize the alert levels from I up to IV. Level I is the lowest alarm level and Level IV is the highest (figure 4).

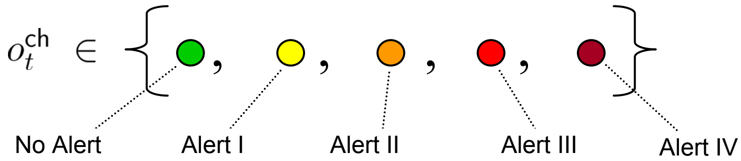


Figure 4: Possible Chemical Outcomes (quantized)

Now 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. This desired information is represented by the probability mass function $p(o_t^{\mathsf{ch}}|a_t^{\mathsf{ch}})$, whereas $a_t^{\mathsf{ch}} = s$ – analogously to the tracking problem – is the association between $\mathbf{z}_t^{\mathsf{ch}}$ and a person s. The probability mass function can be represented by a matrix. The number of rows corresponds to the number of possible classification values for o_t^{ch} and the number of columns corresponds to the number of persons S. So the columns refer to the possible values of a_t^{ch}. Such a matrix is called a confusion matrix (figure 5).

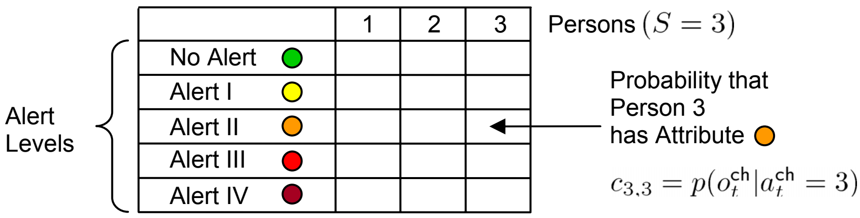


Figure 5: Confusion Matrix

We denote the confusion matrix as $\mathsf{C} = \{c_{is}\}$ with $c_{is} \equiv p(o_t^{\mathsf{ch}} = i|a_t^{\mathsf{ch}} = s)$. So c_{is} is the probability that the classification process will produce the class output i when the observation was in fact caused by person s. As 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

$$\mathcal{Q}(\mathcal{X}, \Pi, \mathsf{C}; \mathcal{X}^l, \Pi^l, \mathsf{C}^l). \tag{12}$$

The iterative estimates for the confusion matrix entries are found by maximizing the $\mathcal{Q}$-function. This leads to the algorithm called PMHT-c. To get PMHT-c the expectation-step (E-Step) and the maximization-step (M-Step) of the basic PMHT have to be extended by the classification estimates. We explain the significant steps as they are applied for our purposes. To make the formulae look clearer, we will write the iteration index l in brackets.

3.2.1 Calculate Assignment Weights (E-Step)

First we have to calculate the posterior assignment probabilities $w_t^{\mathsf{ch}\to s}(l)$. According to the derivation by Davey [4] we use the following update formulae (13).

$$w_t^{\mathsf{ch}\to s}(l) = \frac{\pi_t^{\mathsf{ch}\to s}(l)\cdot\mathcal{N}(\mathbf{p}^{\mathsf{ch}};\mathbf{x}_t^s(l),\mathsf{Cov})\cdot c_{o_t^{\mathsf{ch}}s}(l)}{\sum_{s'=1}^{S}\pi_t^{\mathsf{ch}\to s'}(l)\cdot\mathcal{N}(\mathbf{p}^{\mathsf{ch}};\mathbf{x}_t^{s'}(l),\mathsf{Cov})\cdot c_{o_t^{\mathsf{ch}}s'}(l)} \quad \forall s,\forall\mathsf{ch} \tag{13}$$

These posterior weights reflect the *relevance* of a chemical output for a person s in the surveillance area. As all outputs have a priori the same relevance we set $\pi_t^{\mathsf{ch}\to s}(l)$ to a constant $(\forall s, l)$ which makes them vanish. The posterior assignment weights are mainly governed by the Gaussian $\mathcal{N}(\mathbf{p}^{\mathsf{ch}};\mathbf{x}_t^s(l),\mathsf{Cov})$ which is a measure for the distance between the chemical sensor with index ch and the current track estimate of person s (figure 6).

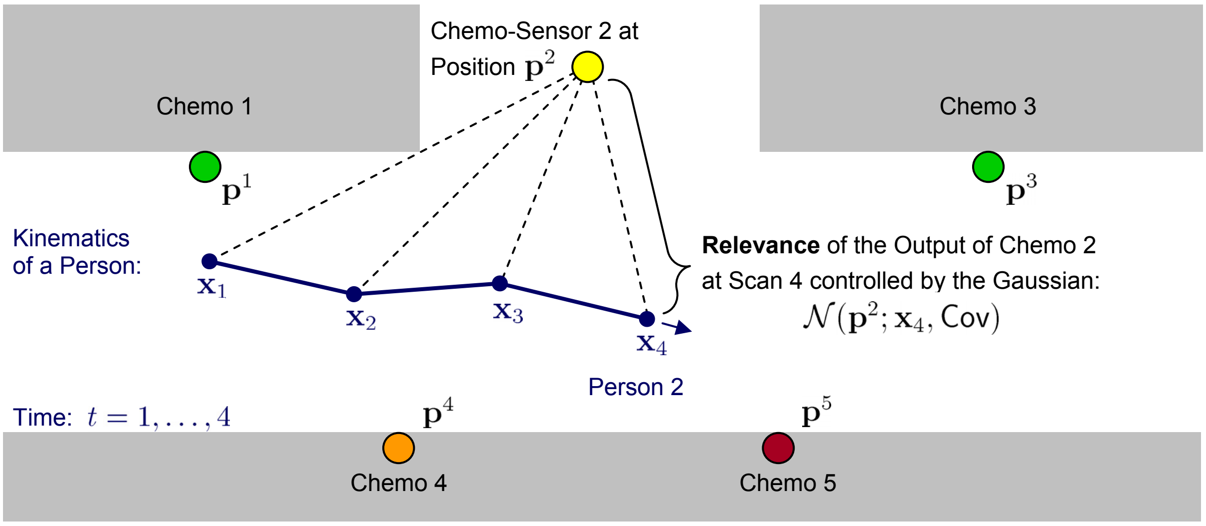


Figure 6: Expectation-Step of the Classification

The corresponding covariance matrix Cov reflects the detection radius of the "chemical nose" and has to be experimentally determined. $c_{o_t^{\mathsf{ch}} s}(l)$ is the current estimate of the confusion matrix entry that associates the output of sensor ch with person s: the probability that s caused a certain alarm (level IV, III, II, I or no alert), which is the probability of carrying dangerous material or not. The posterior weights $w_t^{\mathsf{ch}\to s}(l)$ are calculated for each sensor ch and each person s at each scan of the current PMHT window.

3.2.2 Maximize the $\mathcal{Q}$-Function (M-Step)

During the M-Step our parameter estimates have to be updated. Besides the estimates $\mathcal{X}^l$ and Π^l for tracking purposes we have to update the entries of the confusion matrix. Following [4] this means processing formula (14).

$$c_{is}(l+1) = \frac{\sum_{t=1}^{T}\sum_{\mathsf{ch}=1}^{5}\left(\delta(o_t^{\mathsf{ch}} - i)\cdot w_t^{\mathsf{ch}\to s}(l)\right)}{\sum_{t=1}^{T}\sum_{\mathsf{ch}=1}^{5} w_t^{\mathsf{ch}\to s}(l)} \tag{14}$$

As PMHT-c works on a sliding data window, not only the relevance weights of the current scan are available, but also the whole history inside the time window can be taken into account and evaluated (figure 7).

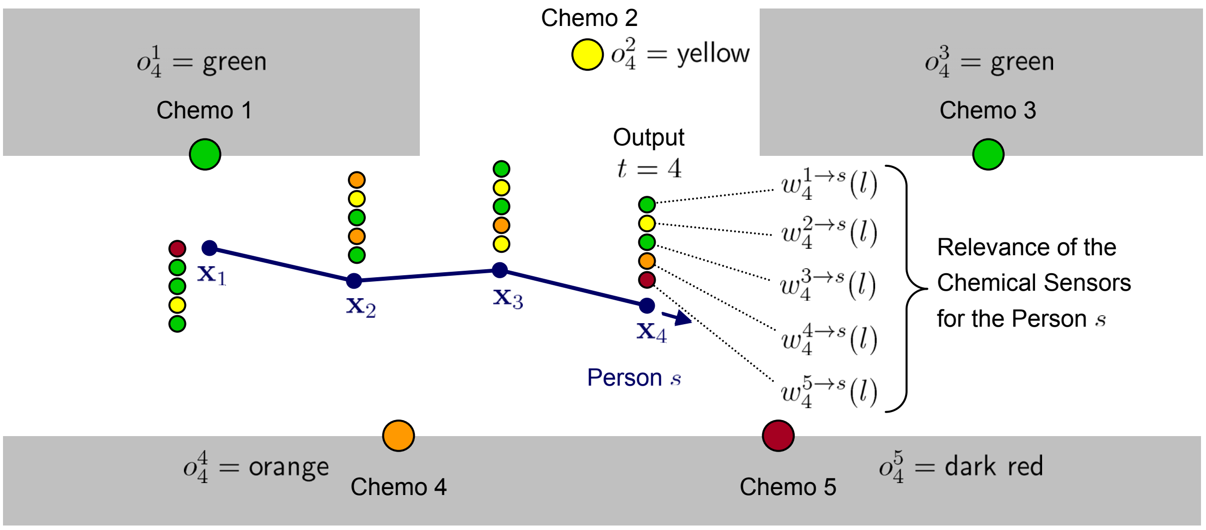


Figure 7: Available Weights for the Maximization-Step of the Classification

To update the classification entry for a certain alert level $\in$ {green, yellow, orange, red, dark red} one has to sum up all posterior weights of sensors that indicate this level. 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 7 we have to calculate

$$\mathsf{Class}(\mathsf{dark\ red}, s) = \frac{w_1^{1\to s} + w_4^{5\to s}}{\sum_{t=1}^{T}\sum_{\mathsf{ch}=1}^{5} w_t^{\mathsf{ch}\to s}}. \tag{15}$$

3.2.3 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.

4.0 EXPERIMENTAL EXAMPLES

In this section we show experimental examples of the PMHT-c processing. We applied the algorithm to simulated scenarios and integrated it in a real demonstrator.

4.1 Simulations

We demonstrate the classification ability of the PMHT-c in the following scenario (figure 8a, 8b): Two persons walk slightly staggered from the left entry to the right entry of the main corridor. The length of the PMHT window was set to 5 scans and a constant number of 4 iterations was processed. A track is extracted when a person enters the surveillance area by passing one of the three entrance areas (light yellow). A track is deleted when a person leaves the surveillance area. At the head of the track we see the sum of all alert probabilities (probability of "being not Green"), that is

$$\sum_{\text{Alert}=\text{I}}^{\text{IV}} c_{\text{Alert},\,s} \tag{16}$$

for a person s. This is the current probability that the person is dangerous. The upper left wall block contains the current classification matrix. The dangerous person is marked by a red rectangle. The chemical sensors react according to the Euclidian distance of the person. The output is quantized as shown in figure 4, so there are the four alert levels symbolized by different colours.

The generated scenario is one of the most difficult tasks for PMHT-c, because the persons have the same walking direction. At the beginning the algorithm wrongly suspects the upper person. The lower person activates Sensor 1, but the upper person is nearer to it at every scan of its PMHT-c window. So it is quite consistent that the PMHT-c associates the dangerousness with the wrong person (figure 8a).

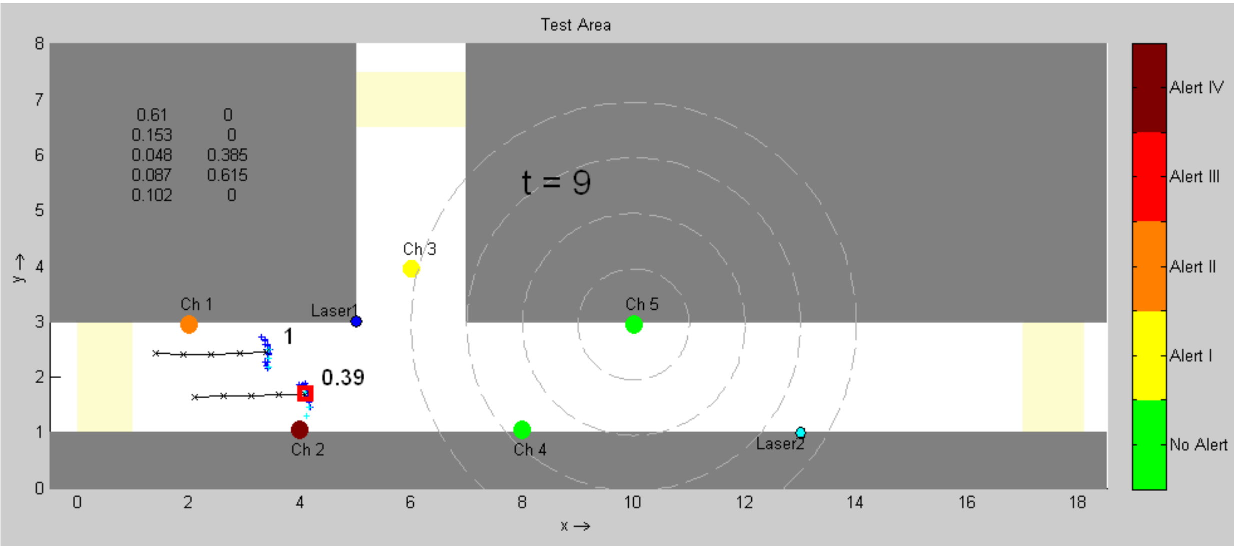
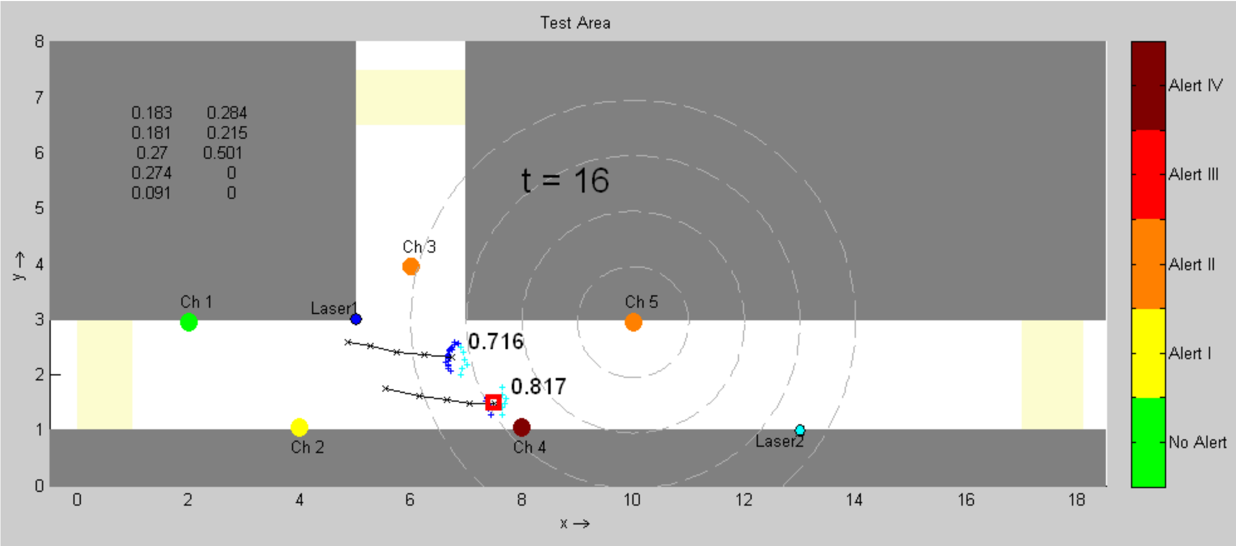


Figure 8a: Simulation with two Persons, Scan t = 9

But as the five chemical sensors are distributed over a large part of the corridor, the algorithm gets more and more information over the time and learns who the true villain is (figure 8b, 8c). Of course such a kind of simulation reflects perfect conditions. It is an idealization of the reality and finding a suitable model for the real reaction of the chemical sensors turned out to be very hard.



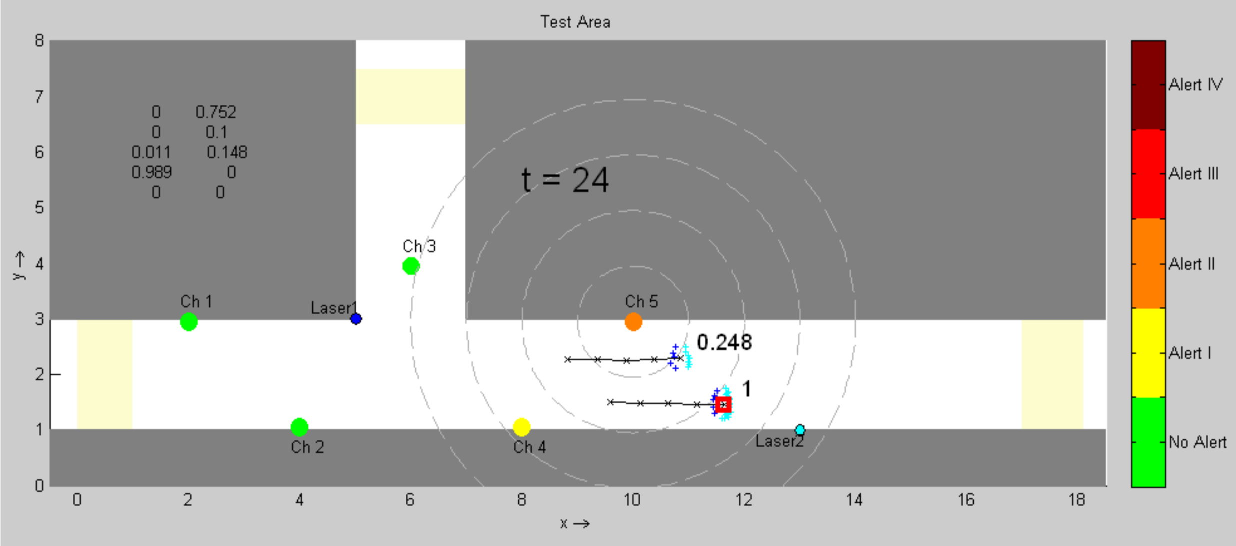


Figure 8b: Simulation with two Persons, Scan t = 16 and t = 24

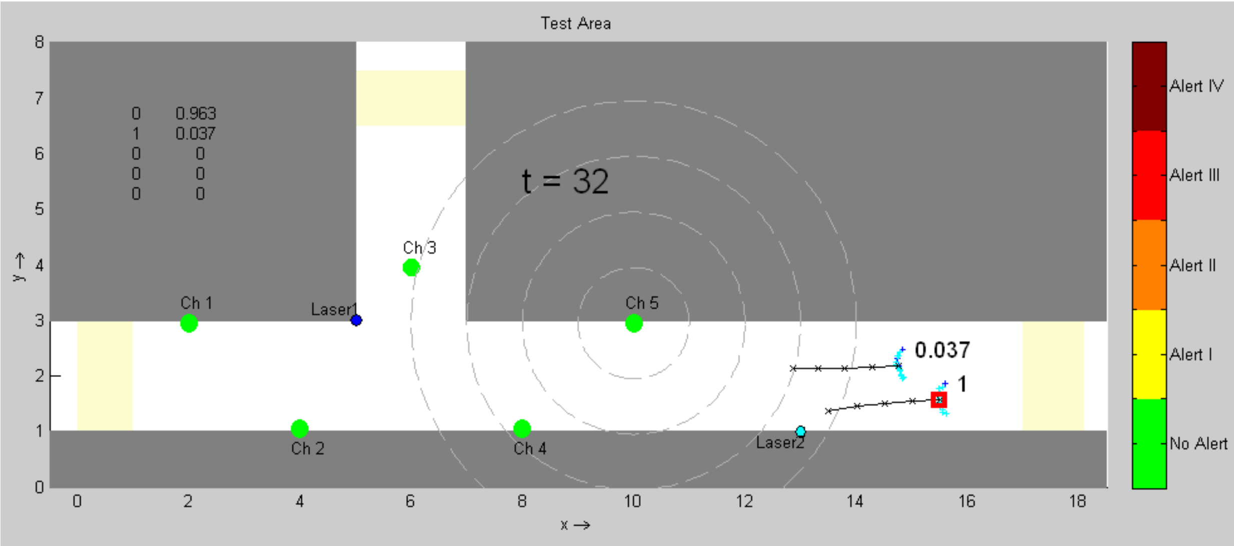


Figure 8c: Simulation with two Persons, Scan t = 32

4.2 Real-Time System

The demonstrator is designed as a corridor containing a U-turn. The aisle has a width of 1.89 m, a height of 2.50 m and total length of 9 m. Ceiling and walls are made of low-emission press board mounted on an adjustable metal frame. The placement of the five chemical sensors can be seen in figure 9. There are two on each side of the "U" and one in the middle. We placed one laser-range-scanner at the entrance, one at the exit and one in the middle below the middle chemical sensor.

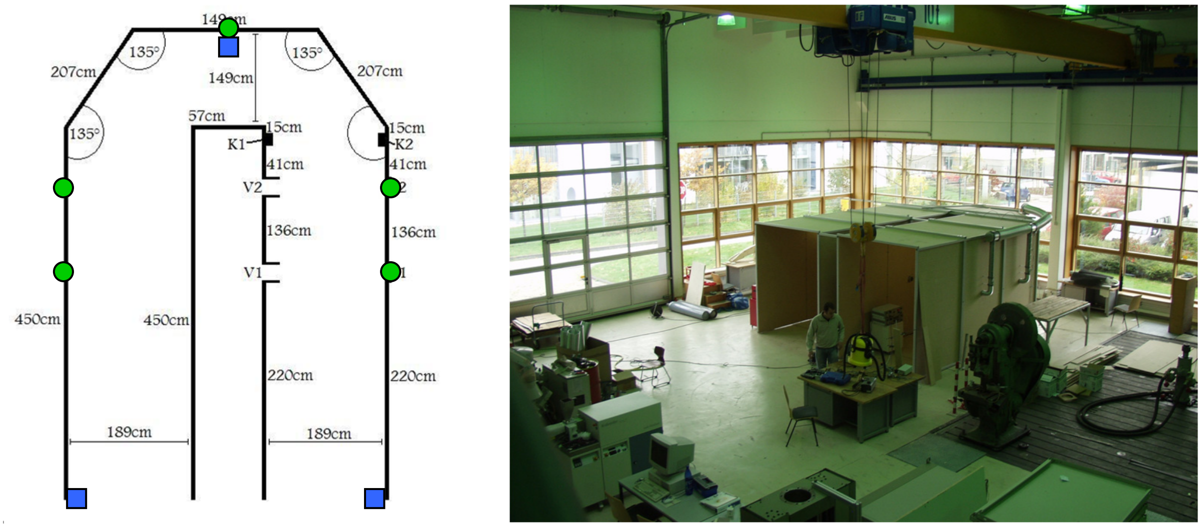


Figure 9: Conceptual Design of the Real-Time Environment

After processing a multitude of tests we were able to empirically analyze the reaction of the chemical sensors. Figure 10 (left) shows the averaged signal of a chemical sensor, when a person passes it at five different distances. To get the complete sensor model we made an area interpolation with cubic splines as shown in figure 10 (right).

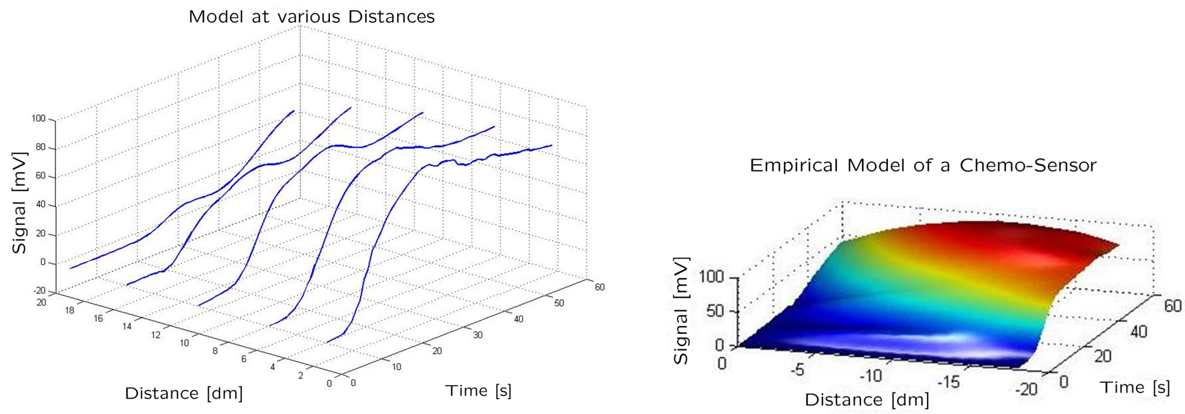


Figure 10: Empirical Model of a Chemical Sensor

The plots clearly show the high delay of about 10 sec which occurs at every of the distances. This delay turned out to be a hard problem in our real-time environment, especially because it varies from time to time and makes the right association very difficult (and sometimes even impossible). To accelerate the reaction of the chemical sensors we integrated them into the air inlet sides of an adjustable air ventilation system (figure 11). The sucking side consists of one air ventilator ($V_{\text{max}} = 1060\,\text{m}^3/\text{h}$) which is connected to four inlet tubes of 100 mm diameter which are 1.36 m above ground. The airflow of the inlets can be adjusted as a whole and separately. On the opposite wall of the air inlets corresponding air blowers ($V_{\text{max}} = 175\,\text{m}^3/\text{h}$ each) are installed. The throughput of each air-blower can be adjusted separately and different sizes of nozzles can be attached.

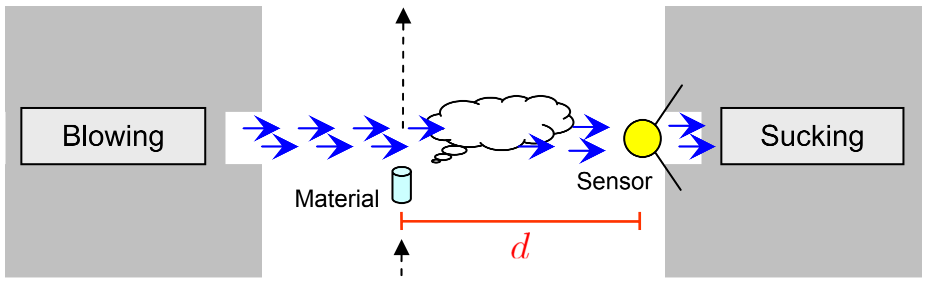


Figure 11: Air Ventilation System

Using this ventilation system we were able to reduce the average delay from 10 sec to 6 sec but could not increase the controllability of the delay. It can vary from 5 sec up to 8 sec so that the correct association cannot be guaranteed. Nevertheless we were able to achieve some good results when the persons were walking well separated and slowly enough. Figure 12a and 12b show some snapshots of a real scenario with two persons. The values at the head of the tracks are the not normalized weights after the last iteration.

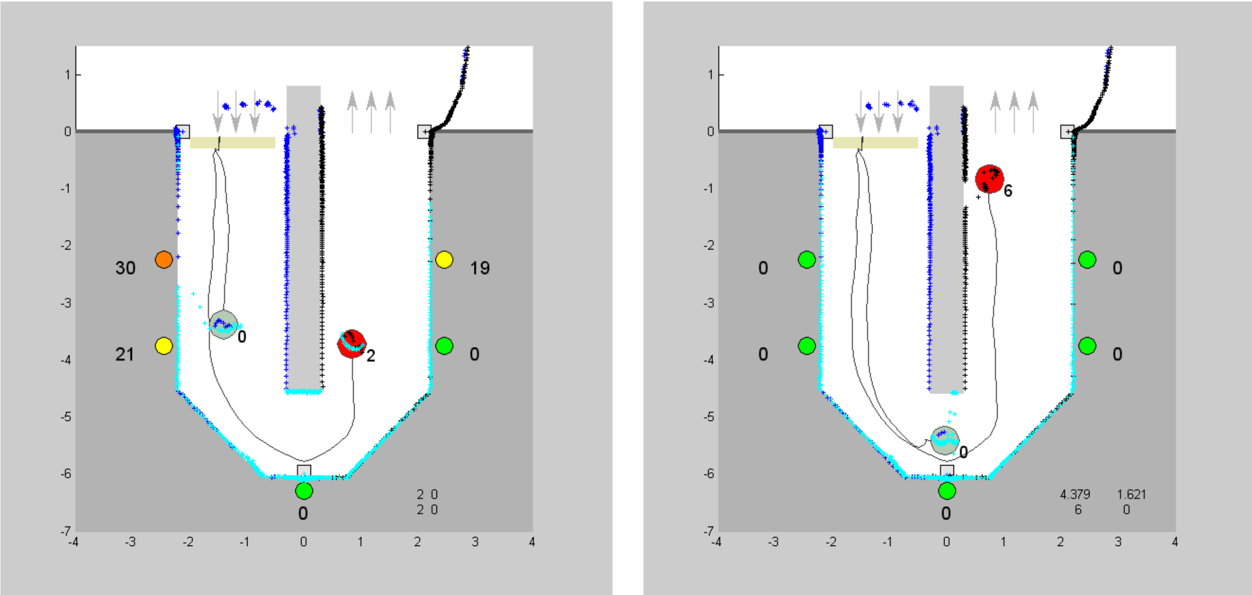


Figure 12a: Snapshots of our Real-Time System

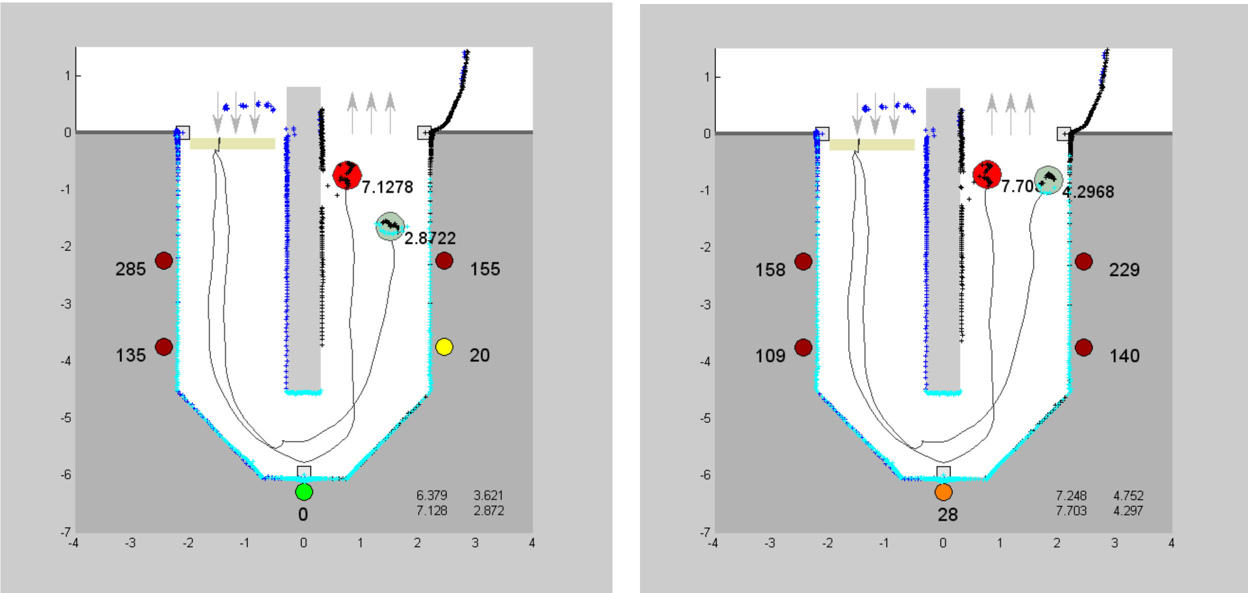


Figure 12b: Snapshots of our Real-Time System

5.0 SUMMARY AND FUTURE WORK

We showed how PMHT-c can be applied for the purpose of a combined person tracking and classification in the context of a security assistance system. Under perfect conditions – especially no delay or at least constant (computable) delay of chemical sensors – this algorithm can achieve reliable classification results.

However, regarding our real-time environment, much more experiments are necessary to find a suitable model of the chemical sensors. Air circulations and streams caused by the persons' movement will play an important role. Especially the velocity of the walking persons influences the chemical reactions. Also temperature and humidity could be topics that have to be examined. Furthermore the exploitation of the different alarm levels will be a part of our future work. Of course this all can be improved by better chemical sensors that have to be developed by the chemists. The progress of this approach is dependent on the progress in the development of faster and more selective chemical sensors.

6.0 REFERENCES

[1] Bar-Shalom, Y., Fortmann, T. E., *Tracking and Data Association*, Academic Press, 1988.

[2] Blackman, S. S., Populi, R., *Design and Analysis of Modern Tracking Systems*, Artech House, Boston (USA), 1999.

[3] Blackman, S. S., *Multiple-Target Tracking with Radar Applications*, Artech House, Boston (USA), 1986.

[4] Davey, S. J., *Extensions to the Probabilistic Multi-Hypothesis Tracker for Improved Data Association*, University of Adelaide, Dissertation, 2003.

[5] Dellaert, F., *The Expectation Maximization Algorithm*, Tech. Report, College of Computing, Georgia Institute of Technology, GIT-GVU-02-20, http://www-static.cc.gatech.edu/gvu/reports/2002/abstracts/02-20.html

[6] Koch, W., Stannus, W., *On Robot-borne Extended Object Tracking*, Forschungsinstitut für Kommunikation, Informationsverarbeitung und Ergonomie (FKIE), FKIE/SDF/2003/66, 2003.

[7] Streit, R. L., Luginbuhl, T. E., *Probabilistic Multi-Hypothesis Tracking*, Naval Undersea Warfare Center Division, NUWC-NPT/10/428, 1995.

[8] Streit, R. L., *PMHT (Probabilistic Multi-Hypothesis Tracking) and Related Applications of Mixture Densities*, Plenary Talk, ISIF – 9th International Conference on Information Fusion, Florence (Italy), 2006.

[9] Tanner, M. A., *Tools for Statistical Inference*, Springer Verlag, Berlin (Germany), 1996.

[10] Wieneke, M., Koch, W., *The PMHT: Solutions for Some of its Problems*, SPIE - Conferences of Optics and Photonics (Signal and Data Processing of Small Targets), San Diego (USA), 2007.

[11] Wieneke, M., Koch, W., *On Sequential Track Extraction using Expectation-Maximization*, EURASIP, Special Issue “Track Before Detect Algorithms”, 2008.

[12] Willett, P. K., Ruan, Y., Streit, R. L., *PMHT: Problems and Some Solutions*, IEEE Transactions on Aerospace and Electronic Systems, vol. 38 , no. 3 , pp. 738-754, 2002.