# The Z-Tracker Personal Emergency System (PES): An Adaptive Machine Learning Location System based on GPS-Tuple

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**Abstract.** Machine adaptive methods allow the analysis of various GPS-parameters (tuple) in order to track the movements of human beings and to distinguish their positions from critical to uncritical working environments inside a petrochemical plant. A programmed learning capability has been implemented into the prototypic Z-Tracker-Personal-Emergency-System (PES), based on the Naive Bayes Classification of GPS-related signal pattern. In this context each pattern can be taken as typical for a covered or non covered working environment. Step by step the PES gains a deeper knowledge regarding to typical, whereabouts within the infrastructure of an industrial plant depending on specific GPS signal pattern and their related probable type of working environment. The System is able to decide whether a new tuple pattern represents an uncritical, tractable movement (class) of a person or a highly critical steady state position (class) after a vital accident due to an emergency. As a direct consequence of the learning process mathematical regularities can be deduced for each possible location scenario. Field studies in the Leuna Refinery (Germany) revealed a high reliability of the Z-Tracker-Personal-Emergency-System.

**Keywords.** Z-Tracker, GPS, adaptive positioning system, signal pattern, Naive Bayes classification, emergency, refineries.

## 1. Introduction

In an industrial complex like a petrochemical refinery a high potential of hazards does exists concerning the personal safety of the service crew. The periodical maintenance cycles of such plants are given by German law (*Behälterverordnung*) [1] and are called *turnarounds*. The potential hazards for the field staff increases during the beginning and the end of such maintenance breaks due to the shut down and the following start up of the system: first, the refinery is in an unstable process line and second, third party service specialists might necessarily enter the plant environment for repairs during a *turnaround*. This leads to the requirement that the position of every personnel inside the refinery has to be known to the plant security service for movement monitoring especially in case of emergencies [2].

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The Z-Tracker-PES offers a possibility to locate moving objects in the plant and to classify their positions regarding to emergency situations. It consists of the Z-Tracker-GPS-handheld device (to track and locate a person) and the Z-Tracker-Background Analytical System (to evaluate and visualize the received position statements).The position of a person is calculated by the integrated GPS-chip [8][9] of the handheld device and transmitted via the public mobile communication network to the Z-Tracker-Background Analytical System (Figure 1).

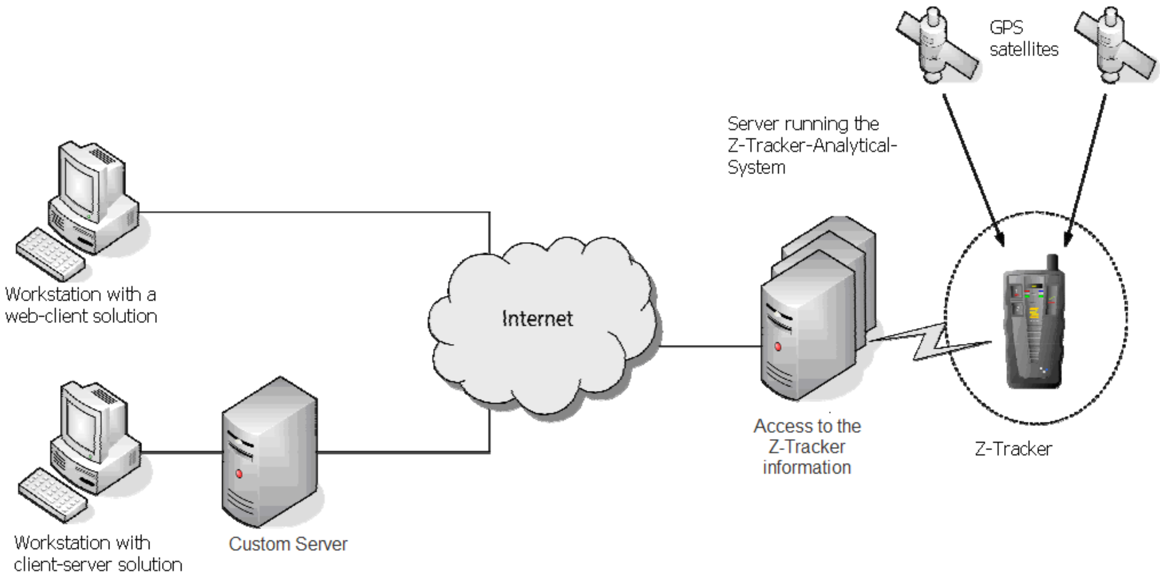


Figure 1: Components of the Z-Tracker-Personal-Emergency-System (Z-Tracker-PES)

The characteristic type of environment within the refinery, i.e. piping, constructions, containers or bearing structures, which possibly surrounds a candidate person affects its positioning in the way that the calculation of the GPS data exhibits a typical location failure (hereby assigned to *covered* and *not covered* positions inside the refinery, Figure 2). In order to detect and to classify such failures in the positioning of personnel the adaptive machine learning concept of the *Naive Bayes Classifier* has been applied to the PES [5]. *Covered* and *not covered* positions are defined as two possible location classes. The classification process is based on an adaptive knowledge base, where each new position contributes its failure features in terms of its uniqueness to one of these two classes. Each possible class is defined by typical *attribute tuples* (see chapt. 2.2). Thus the integrity of the knowledge base increases with every new calculated position.

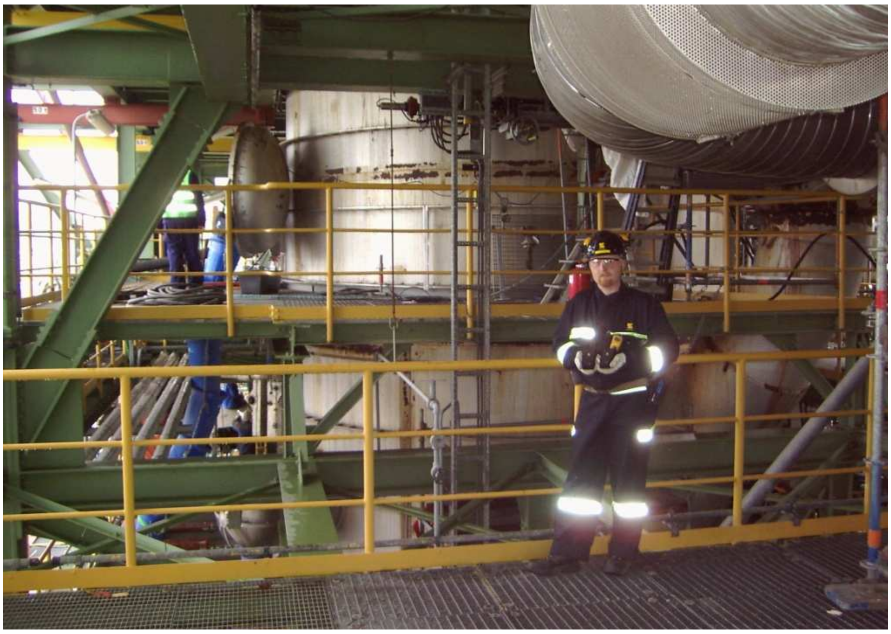

Figure 2: Service personnel within a covered environment of a refinery

## 2. Naive Bayes Classifier

The basis of the *Naive Bayes Classifier* (*NBC*) is the Bayes Theorem (1) which allows calculations considering conditional probabilities.

$$P(h|D)=\frac{P(D|h)P(h)}{P(D)} \tag{1}$$

The *NBC* is a supervised learning method and is well proven for other purposes which classify instances by a tuple of attributes to predefined classes. It has to be stated that the results of the *NBC* are as good as other comparable algorithms, like neural networks or decision trees [6].

### *2.1. Functional Principle*

Applying the *NBC* means to describe every instance X by a tuple of attributes $a_i$. In a target function these attributes are to be classified representing the instance X and is therefore able to represent every possible class.

The attributes of an instance should be similar and conditional independent to each other. In reality this norm is not often realized because most attributes affect each other in various mutual ways. Anyhow, even if the naive conditional independence assumption is not fulfilled totally in the model the *NBC* shows a quite good performance [8], mainly because the learning method is based on step by step obtained knowledge. That means the amount of instances as well as the describing attribute tuple and the resulting classification of the instances are well known. The attribute's frequency of the test volume allows the calculation of probabilities for each type of tuple.

At this point the membership of each new, unknown class to every possible class will be calculated and as a result the instance will assigned to the class with the highest likelihood of membership. The function of the *NBC* in this case is as follows:

$$v_{NB} = \arg\max_{v_j \in V} P(v_j) \prod_i P(a_i \mid v_j) \quad (2)$$

Where $P(a_i \mid v_j)$ represents the single probability of the attribute to be assigned to the class $v_j$ . The product of all $\mathbf{a_i}$ is the probability of each class $v_j$ , where $\arg\max$ represents an unknown instance and its association to the most likely classification [5].

The classification of *covered* and *uncovered* locations is represented by the same binary classes and an unknown instance is classified into these classes by the target function.

### *2.2. Attribute Tuple*

As mentioned above an attribute tuple characterizes an instance and with regard to the calculation of the correlation coefficient and the rank correlation coefficient respectively [2] (Table 1). The PES exploits the following attributes (which are

| Rank correlation coefficient | | | | | | |
|---|---|---|---|---|---|---|
| | SNR | PDOP | HDOP | VDOP | Number of Satellites | Position-Fix |
| SNR | | 0.2073918 | 0.3147014 | 0.1481973 | 0.2600889 | 0.1804896 |
| PDOP | | | 0.6943445 | 0.884425 | 0.6503072 | 0.1239844 |
| HDOP | | | | 0.4442993 | 0.6868587 | 0.1670893 |
| VDOP | | | | | 0.4869474 | 0.03685033 |
| Number of Satellites | | | | | | 0.2290039 |
| Position-Fix | | | | | | |

Table 1: Matrix of the rank correlation coefficient for the GPS-attributes to get the most sophisticated attributes [2]

collected simultaneous to the corresponding GPS coordinate data):

- *Signal to Noise Ratio (SNR)*
  This attribute mentions the ratio between the received GPS-Signal and the background radiation (noise) [7]
- *Dilution of Precision (DOP) – PDOP – VDOP – HDOP*
  The DOP values describe the failure which depends on the geometrical position of the used GPS satellites in respect to the GPS receiver. The overall PDOP can be slivered into the HDOP (horizontal) and the VDOP (vertical) component [7]
- *Number of used satellites for localization*
  This is the count of satellites which has been used to calculate the GPS position
- *Type of the Position-Fix*
  The Position-Fix presents a value which means that a GPS-Position is a three-dimensional, two-dimensional or an estimated position

| | | | | | | |
|---|---|---|---|---|---|---|
| Calculation of the single value possibilities in regard to their counting | | | | | | |
| **Class: “not covered locations”** | | | | | | |
| Parameter: ***SNR*** | | | Number of classes: ***13*** | | Number of values: ***1047*** | |
| ***x*** – Class Instance by Value; ***n*** – counts of measurements; **h** – possibility of the instance with regard to the counting and the whole measurements; ***F*** - added single possibility; ***NBh*** – possibility of each instance with regard to the Naïve Bayes (avoiding zero possibilities); ***NBF*** – added single possibility | | | | | | |
| | X | n | h | F | NBh | NBF |
| 1 | 1 | 1 | 0,001 | 0,001 | 0,002 | 0,002 |
| 2 | 36 | 1 | 0,001 | 0,002 | 0,002 | 0,004 |
| 3 | 38 | 3 | 0,003 | 0,005 | 0,004 | 0,008 |
| 4 | 39 | 2 | 0,002 | 0,007 | 0,003 | 0,010 |
| 5 | 40 | 5 | 0,005 | 0,011 | 0,006 | 0,016 |
| 6 | 41 | 33 | 0,032 | 0,043 | 0,032 | 0,048 |
| 7 | 42 | 87 | 0,083 | 0,126 | 0,083 | 0,131 |
| 8 | 43 | 225 | 0,215 | 0,341 | 0,213 | 0,344 |
| 9 | 44 | 279 | 0,266 | 0,607 | 0,264 | 0,608 |
| 10 | 45 | 208 | 0,199 | 0,806 | 0,197 | 0,806 |
| 11 | 46 | 154 | 0,147 | 0,953 | 0,146 | 0,952 |
| 12 | 47 | 43 | 0,041 | 0,994 | 0,042 | 0,993 |
| 13 | 48 | 6 | 0,006 | 1.000 | 0,007 | 1,000 |

Table 2: Matrix of the calculated possibilities of the SNR attribute for not covered locations resulting in 13 classes

### *2.3. Training of the NBC and the PES System*

The *NBC* implemented in the PES is trained by known sample GPS data representing specific test scenarios. (thereby the probability for all attributes will be assigned; Table 2 is an example of the calculation of the probabilities for the SNR). This is achieved by counting the single parameter values in the distribution from each attribute (NBh = single probability). Afterwards the training will be improved by another sample of the validation data (test scenarios) being discrete to the training data collected by the Z-Tracker (Figure 3).

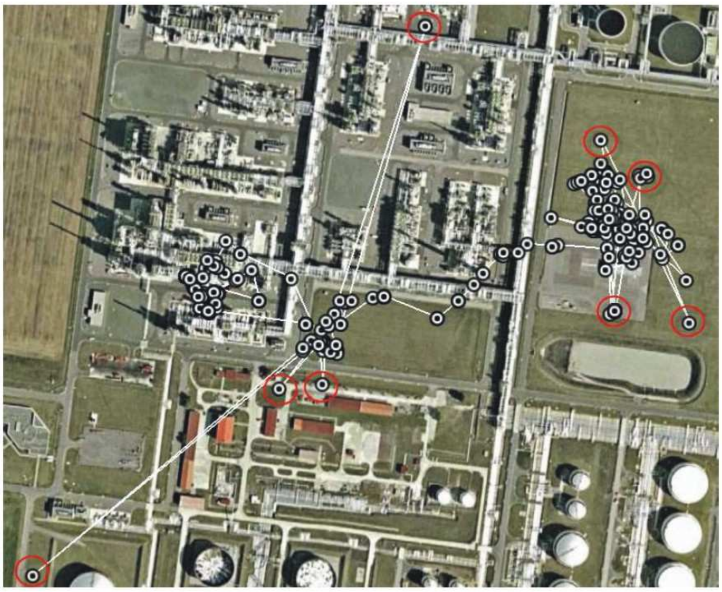

Figure 3: Aerial photograph of a refinery showing the position of sample data for training aspects

### *2.4. Evaluation of the adaptive learning method*

The performance of the machine learning is estimated by a confusion matrix. The matrix is with regard to the two possible classes covered and uncovered situations divided in two columns and two rows. The expected value is signed into the columns

and the estimated value into the rows. The main diagonal represents the correct matches while the mismatching values are located aside of them. By counting the right and false matches one is able to validate the performance of the learning.
Therefore the expected and the estimated value of the *covered* and *not covered* classes are set into relation. The best combination of attributes to classify an instance was the *SNR* and the *Number of used satellites,* in this particular case containing only one misclassified instance (Table 3).

It became clear that other combination of attributes (tuple), for instance the performance of *PDOP* and *Number of used satellites* (Table 4) leads to a less reliable result.

| Expected value / estimated value | Not covered | Covered | Performance (%) |
|---|---|---|---|
| Not covered | 347 | 1 | 99,86 |
| Covered | 0 | 350 | |

Table 3: Matrix of the classified validation cases applying SNR and of the number of used satellites for covered and not covered locations

| Expected value / estimated value | Not covered | Covered | Performance (%) |
|---|---|---|---|
| Not covered | 303 | 45 | 73,50 |
| Covered | 140 | 210 | |

Table 4: Matrix of the classified validation cases applying PDOP and of the number of used satellites for covered and not covered locations

## 3. Conclusion

This study underlines that machine learning methods, if implemented into GPS movement monitoring systems like the Z-Tracker PES, are able to distinguish between uncritical *not covered* and critical *covered* positions of personnel within an industrial plant like a refinery. In this context the *NBC* has been proved as a reliable method to evaluate GPS measurements in order to gain information about the potential spatial hazards for employees within their working environment.

One of the future requirements which can be deduced from this prototypic model is the applicability of the PES regarding to other types of petrochemical plants or any other industrial complex with an ‘endemic’ local primary spatial location systems: In that case: Is it possible to apply the same kind of *NBC*-knowledge base or should the system be trained by additional data (satellite or terrestrial signals) to achieve a more differentiated knowledge about an instance or location? Could this additional information be measured by the Z-Tracker or other handheld devices (like a GPS-phone or a data-logger)?

Also new developments in the (D) GPS/Galileo Systems might increase the capability of the Z-Tracker-PES, like the exploitation of differentiated frequencies or a faster and higher mobile data communication. Further applications of a *NBC*-trained location system are likely in the entertainment industries or special health services.

## Formulas



## Figures



## Tables



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