Reliable situation recognition based on noise levels

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Abstract

Situation recognition based on audio signals can be used to determine situations in a meeting room while protecting the privacy by recording and analyzing only the noise level instead of the complete audio signal.

A reliable situation recognition is normally obtained using Bayesian networks which do not only rely on context information itself but additionally on corresponding probabilities. Especially when the situation recognition itself should output a quality rating to the determined situation it is necessary that each analyzed information about all preconditions is rated with qualities or probabilities. This leads to the need of a conversion from uncertainty to probabilities when using sensor data to observe the environment to recognize situations.

In this paper we compare different methods for situation recognition based on noise level measurements. We implemented a Multilayer Perceptron Neural Network, a simple empiric method and we describe the advantages of our method based on multinomial logistic regression which we adapted to a reliable and easily configurable situation recognition based on sensor data. To evaluate the methods we distinguished between the situations meeting, work and silence and recorded thousands of noise levels to calibrate and compare the different methods against each other.

Our approach using logistic regression can be used as situation recognition based on sensor data. It is not necessary that the input information contains quality ratings but the system has to be calibrated with sensor data that can be assigned to all the situations that have to be distinguished. Since the result of this method contains probabilities to all situations it can also be used to analyze sensor data related to single preconditions of complex situation recognition algorithms based on Bayesian networks and different types of context information.

Keywords: sensor, situation recognition, probability, logistic regression, quality, context.

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1 Motivation: situations and probabilities

Situation recognition based on context information is described for example in [1] and [2] where situations are predefined by conditions. Situation recognition in general combines learned knowledge and observation of the environment. A matching algorithm has to determine which predefined situation fits best to the current state of the world or to the environment of an application or it's user. The learned knowledge in this case can consist of situation templates [3] that are configured by users or application designers or it can be the result of learning algorithms that cluster context information.

Situation templates are arranged in situation libraries for different context aware applications. It is common that situations concerning the same use case have overlapping preconditions or are correlated with the same phenomenon in the environment but for each situation template with different attributes. To detect a meeting in a room for example a noise level could be used. In this example the same phenomenon would be used for the detection of a meeting where the noise level should be above a defined threshold or for the detection of a situation where some people work in a room and the noise level should be below a defined threshold. To get a more reliable system the situation detection normally is done via Bayesian networks which do not only rely on the noise information itself but additionally on corresponding probabilities. Especially when the situation recognition itself should output a quality rating to the determined situation it is necessary that all the analyzed information to the preconditions are rated with qualities or probabilities. A situation recognition that provides probabilities to each possible situation therefore needs probabilities to each information that is assigned to a precondition. This leads to the need of a conversion from uncertainty to probabilities when using sensor data to observe the environment to recognize situations.

2 Related work

A probabilistic databases [4] have been developed to handle uncertainty in databases using possible worlds semantics. These databases handle uncertainty accurately and efficiently. Several models for uncertainty and updates from sensors are described and listed in [5] where uncertainty is processed as probabilities to certain ranges surrounding a measurement of a sensor.

Situation recognition based on sensor data is often done using Bayesian Networks [6, 7] or using more complex algorithms that also rely on probabilities [8]. To distinguish between several possible situations it is often necessary to rate all the defined preconditions or to assign sensor data to different conditions. Therefore probabilities are used to combine context information to determine a situation.

The missing link between the probabilistic databases or the situation recognition and the raw sensor data is the conversion from absolute, relative or standard deviations of the sensors to corresponding probabilities to measurements.

3 Sensor data and degradation

3.1 Augmented world model, degradation and stochastic errors

The Nexus platform [9] provides access to context which is managed in distributed augmented environmental models. To extend the environmental models or to update the models to adapt them to the current state of the real world not only user input is used but also sensor data. The platform provides services for reliable sensor data integration by *SensorContextServers* which offer raw and processed sensor data together with ratings such as relative, absolute or standard deviations to context aware applications.

Uncertainty of sensor data is represented in meta data which is divided into several domains of degradation [10] concerning different aspects of quality like temporal aspects, cross sensitivity or stochastic errors. Since in the nexus platform sensors can be used for different applications. Therefore there is no simple possibility to rate the quality of measurements since quality ratings always have to be related to certain requirements. On a *SensorContextServer* the quality of a measurement is rated in relation to the physical attributes of a sensor itself as long as there is no other specification from an application. For example when a physical sensor has a sampling rate of 10 Hz but the value for applications provided by the *SensorContextServer* is updated only once a second then the quality rating concerning timeliness is 10% or 0,1 respectively.

Since each application can have different quality requirements the *SensorContextServer* can manage weights for particular domains of degradation or complete rating specifications based on physical attributes for each application. An application can for example give higher rates for timeliness instead of accuracy to be able to react fast on changes in the environment. The advantage of this quality management by the platform is to shift the effort of quality monitoring from applications on devices to the servers.

Nevertheless we still have only quality ratings for measurements and no probabilities of information that can be used in a situation recognition. A conversion from these ratings to probabilities is needed on the sensor data level. The goal is to obtain information from sensors for preconditions of situation templates. This means for the situation recognition that each single sensor observing phenomena related to a situation is used individually to give a probability to the relevant situation. These probabilities are combined to obtain a reliable situation recognition using all defined preconditions.

4 Conversion from raw sensor data to probabilities

Periods of time

To obtain more reliable results for situations which are not directly related to one single phenomenon in the environment of a user or application we define periods of time in which the related phenomenon is observed.

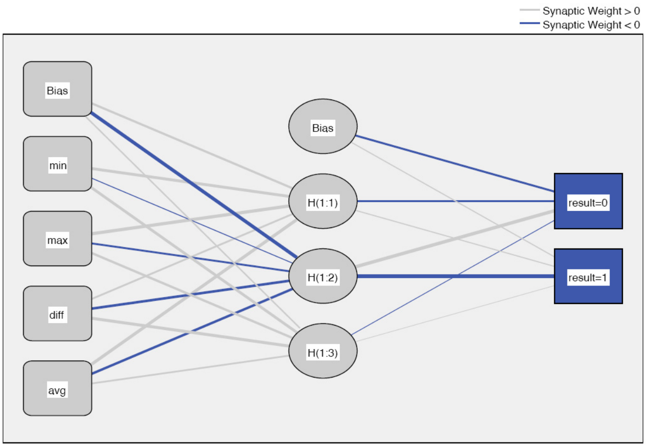

Figure 1: Example of a neural network that uses sensor data to distinguish between two situations.

4.1 Empiric approach

We tested different algorithms to use sensor data for situation recognition. The first approach uses one measurement directly to distinguish between two or more situation templates. This method consists of a lookup table which stores thresholds for each situation that is predefined. These thresholds could be set by a user based on experience or some reference measurements in known situations could be used to assign ranges of measurement results to situations. To generate a probability to a determined situation the position of a measurement within the corresponding interval could be utilized. Even overlapping intervals for the situations could be defined. To learn the lookup table and generate probabilities simultaneously it would be possible to use fuzzy clustering [11] on reference measurements as used in [12] to rate each detected situation.

4.2 Neural network

Another method to determine situations is based on a neural network. Figure 1 shows an example of a multilayer perceptron which uses a bias neuron and *minimum*, *maximum*, *difference* between minimum and maximum and an *average* value of measurements from one sensor divided into periods of time. The output layer consists of two possible solutions, each representing a situation. This approach can be used to assign situations to measurements but it is not suitable to generate a probability or other rating to the determined situation because the output of the neural network is binary.

4.3 Logistic regression

A logistic regression [13] can be used to determine the probability for an occurrence of an event. Adapted to a situation recognition this can be used to determine probabilities for situations or probabilities for single preconditions of situation templates by learning the assignment of reference measurements to known predefined situations.

As input to a binary logistic regression we used the same information from the periods of time as we used for the neural network approach. The logistic regression learns weights called *regression coefficients* by a maximum likelihood estimation to all the input variables corresponding to the derived information of each period of time. The learning is based on reference measurements where the outcome of the logistic regression is already known. In practice a test set of measurements has to be generated where each measurement can be assigned to one of the situation templates manually. A linear combination of the measurements x_j and the corresponding weights β_j is given in equation (1). A situation is assigned to the result z or underlying measurement respectively when $z > 0$. To obtain a quality rating to the determined situation z is normalized to the interval $]0;1[$ as shown in equation (2).

$$z = \beta_0 + \sum_{j=1}^{n} \beta_j * x_j \tag{1}$$

$$p(y=1) = \frac{1}{1+e^{-z}} \tag{2}$$

The binary logistic regression is only suitable for distinguishing two mutually exclusive situations or for determining if one single situation is valid or not. In these cases the sum of the according possibilities calculated as described above is one. To distinguish between more than two situations a Multinomial Logistic Regression is necessary [14]. The adapted calculation of all the probabilities for n situations is given in equation 3 which again normalizes the probabilities to a sum of one.

$$\ln \frac{P(y_{i=m})}{P(y_{i=1})} = \beta_{0m} + \sum_{k=1}^{n} \beta_{mk} x_{ik} = Z_{mi} \tag{3}$$

The more reference measurements are available the more accurate is the situation recognition in the end. Several quality criterions such as Nagelkerke R^2 [15] can be used to check the quality of the regression with the learned coefficients by applying the system to the reference measurements again. This can be used as a general quality monitoring for situation libraries adapted to individual use cases. The corresponding quality is a hint for application designers or applications that automatically adapt situation recognition to reference measurements stating the need for additional reference information to learn the parameters for the algorithm more precisely.

The ratings for our *meeting* example lead to the usage of the difference of a maximum and minimum measurement and the average of the period of time. The

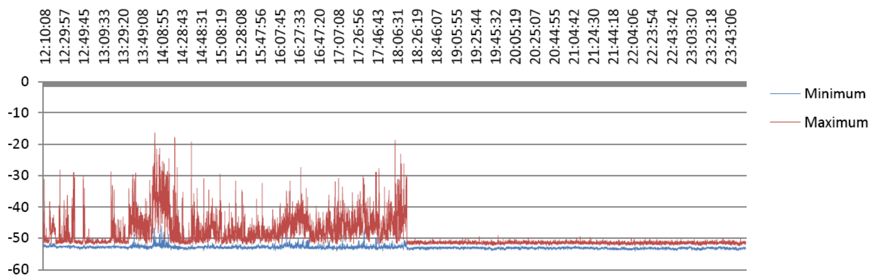

Figure 2: Example of noise levels recorded for a period of 12 hours in dB.

maximum and minimum values themselves were excluded automatically from the situation recognition in our example presented in the next chapter.

5 Evaluation – meeting in a bureau

5.1 Implementation

The methods presented above for situation recognition are implemented on a small Debian Linux operated NSLU2 running a *SensorContextServer*. This device, normally used to attach USB Storage devices to networks, with the size of only $10 \times 14 \times 3$ cm can be placed easily in a room to detect several situations. The possibility of attaching several USB devices enables the usage of a multitude of sensors for which Linux drivers are available. The measurements and results of a situation recognition can be provided by an augmented world model language via internet protocols, which is the interface to our *SensorContextServer*.

The set of situation templates for the evaluation of our situation recognition based on noise levels in a bureau consists of *silence*, *work* and *meeting*. The example shall prove the possibility of situation recognition using one simple sensor. It would be possible to combine several sensors' measurements such as temperature and brightness which are available on our *SensorContextServer* or even an image understanding algorithm using a camera to make the situation recognition more reliable. For our purpose it is sufficient to obtain the classification of a situation based on a single sensor's measurements. This classification including a probability value for the determined situation can be used in complex situation recognitions combining multiple preconditions.

5.2 Reference measurements and noise levels

To recognize the situation of a meeting in a room a soundcard and a simple microphone without noise reduction was attached to our *SensorContextServer* and recorded noise levels over a period of over 70 hours for a test set of reference measurements. One extract of this test set is shown in Figure 2.

To initialize the different methods of situation recognition it was necessary to assign the situations to the measurements of the test set.

5.3 Results and reliability

In a first simple test only *silence* and *meeting* had to be distinguished by the different methods. The detection of the third situation work in the nexus laboratory was more difficult since the noise levels during the situation *work* are very close to the ones from the situation *silence*. Therefore the period of time which was used to obtain a minimum, maximum and average noise level was varied. It turned out that a period of 5 seconds was enough to bridge the gaps in noise levels during work time and to distinguish the situation work from silence for most of the presented methods. Longer periods of time make it easier to distinguish the situations in our example but they should be kept short in order to prevent delays in the situation recognition. An extract of measurements for all situations is shown in Figure 3. The lower part of the diagram shows the directly derived data of the noise levels in dB. The graph combines extracts of 200 measurements from the situations *silence*, *work* and meeting. The upper part of the diagram shows the probabilities for all situations. The situation recognition in our example is unambiguous only for the *meeting* in the last third of the diagram. Here the probabilities are 1, 0 and 0. For the situations *silence* and *work* the recognition is not unambiguous but the obtained probabilities can be used for a reliable assumption of the situation which is shown in the tables containing the detection rates.

A comparison of the presented algorithms is shown in Tables 1 and 2. 1000 measurements of each situation were used to compare the different methods for

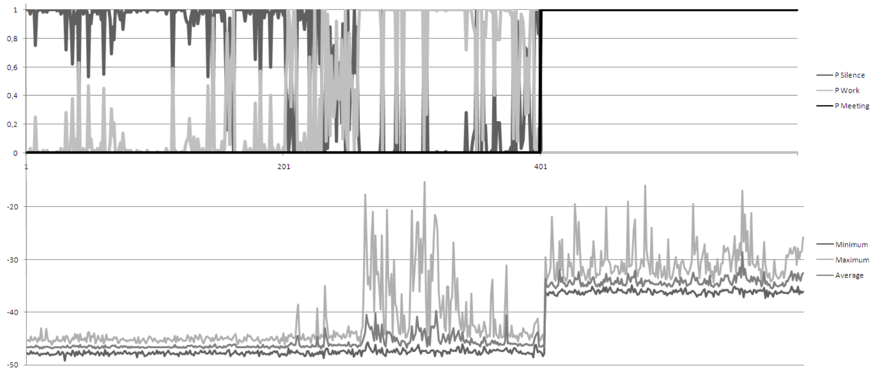

Figure 3: Lower part of the diagram: Combined extracts of 200 measurements each for the situations *silence work* and *meeting* in dB. Upper part of the diagram: Assigned probabilities for the situations by the adapted logistic regression.

Table 1: Detection rates for the *meeting* example with two situations.

	Empiric 30s	**Empiric 5s**	**Neural Network**	**Regression**
Silence	1,000	0,882	1,000	1,000
Meeting	0,880	0,660	1,000	1,000
Total	0,940	0,771	1,000	1,000

Table 2: Detection rates for the *meeting* example with 3 situations.

	Empiric 30s	**Empiric 5s**	**Neural Network**	**Regression**
Silence	1,000	0,882	1,000	1,000
work	0,868	0,658	0,802	0,782
Meeting	0,880	0,660	1,000	1,000
Total	0,916	0,733	0,919	0,912

situation recognition. Table 1 shows the detection rates for only two situations using an empiric method with a period of time of 5 and 30 seconds and the neural network and the logistic regression method, each using periods of time of 5 seconds.

Table 1 shows that the methods using training for the situation recognition do not fail in detecting the situations for all periods of time in this simple example where only silence and meeting had to be distinguished.

The total detection rates in table 1 show that the artificial neural network is a little more accurate in detecting the situations. But since this recognition does not provide any probabilities or quality measures for the current situation it is not feasible for our purpose. The Multinomial Logistic Regression in contrast provides the necessary information about the quality of the detection. The detection rates are marginal below the ones from the neural network. For the empiric method it would be necessary to extend the period of time the measurements are based on from 5 seconds to 30 seconds to obtain detection rates that are comparable to the other systems. But since the extension of this period leads to delays in the situation recognition when adapting the changes of the real world the logistic regression is much more feasible for our purpose. Therefore we use the implementation of the Multinomial Logistic Regression in the Nexus Platform for situation recognition based on measurements or for the calculation of probabilities to preconditions for situation templates accordingly.

6 Adoption to new situations

The logistic regression system has to be adopted and trained with new coefficients whenever a new sensor is involved or new situations have to be recognized. The advantage is that an application designer doesn't have to specify the ranges of values from measurement results that belong to each new situation. It is only necessary to assign the sensors to known situations. The disadvantage is that the systems needs several reference measurements for each new situation to be trained. But once the reference measurements are available the coefficients can be trained in short time. For our example of 3 Situations and more than 50000 measurements the coefficients could be trained in less than 5 seconds on a normal pc. The different training methods *Enter*, *Forward selection* and *Backward Selection* did not make any difference in the result. All trained coefficients lead exactly to the same situation recognition probabilities.

To execute the situation recognition on different devices the trained coefficients could be provided by the nexus platform. This enables a distributed situation recognition where each sensor's measurements can be assigned to preconditions of situations on the device the sensor is attached to. Afterwards only the calculated probabilities have to be communicated over the network.

7 Conclusion

In this paper we present a possibility to use sensor data for situation recognition which provides probabilities to the detected situation. This is necessary in an open system which provides environmental models to context aware applications where the models are updated and extended by measurements. The algorithms assign situation probabilities to single measurements. Therefore it is possible to use complex situation recognition algorithms based on situation templates consisting of probabilities for multiple preconditions.

We compared an empiric method with a neural network and an adapted logistic regression. The comparison is based on an example of a situation recognition that has to detect a meeting in a room based on the noise levels. More than 50000 reference measurements had been recorded to train and test the different methods for the situations *silence*, *work* and *meeting*.

The empiric method provides reliable detection rates only when the period of time which an observation is based on is extended to 30 seconds or more. But this leads to delays in the situation recognition. Comparable detection rates are provided by a neural network for periods of only 5 seconds of observation. This method has the disadvantage of the lack of probabilities that are assigned to the detected situations. For our purpose a multinomial logistic regression, that is adapted to a situation recognition, provides the best results. This method can easily be adapted to new situation templates or new sensors. It even provides a monitoring of the quality of the trained parameters for a particular situation recognition.

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