# A Context Aware System Based on Scent

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## Abstract

*Conventional context-aware systems normally use accelerometers and gyroscopes, and it is difficult to recognize contexts such as having a meal, or going to the toilet. We propose a new context recognition method based on scent using a wearable scent sensor. Since our algorithm considers the characteristics of scent, it recognizes contexts that find difficult to recognize by conventional sensors. Evaluation results demonstrated that scent sensors identify the context of having a meal with 94% accuracy and going to the toilet with 97% accuracy. We also implemented a context-aware life-log system for healthcare.*

## 1. Introduction

There are many context-aware systems using the accelerometer because it can detect the movement of a spatial mounting part and the direction by detecting gravity. However, systems must offer different services depending on whether we are *sitting at our desk at work* or *sitting on a toilet seat*. To recognize such detailed contexts, the system requires not only movement but also the information about the user surroundings such as the condition of the air.

As sensor technologies develop, research is being conducted on reproducing sense organs with a computer. The development of a scent sensor[1] could be put to practical use in various fields such as food science, cosmetics, disaster prevention, and health care. Although, no context-aware systems use scent sensors to improve context recognition in wearable computing environments.

We propose a new context recognition method based on scent using wearable scent sensors, considering the characteristics of scent. Our method recognizes the context, such as *having a meal* and *going to the toilet*, which are difficult to be recognized by conventional methods. We also show that a combination of scent sensors and accelerometers enables to recognizes detailed contexts such as *sitting on a chair on having a meal*.

## 2. Related work

One example of systems combining accelerometers with other types of sensors is LiveNet[2], which uses microphones, EMG, GSR, temperature, pulse oximetry, respiration, blood pressure, EEG, blood sugar, humidity, heat flux, and $CO_2$ sensors. It allows people to receive real-time feedback based on their continuously monitored health state.

Sensor elements sensing scent are classified into two types: gas sensors and biosensors imitating the olfactory function of human beings. The N-SMARTS[3] platforms have pollution gas sensors such as $NO_2$, $SO_2$, and CO sensors. The healthcare field has used biosensors detecting helicobacter pylori on the breath, which causes gastritis and stomach cancer, and detecting a special scent element emitted by breast cancer patients[4]. For these examples, some systems use scent sensors while no system available uses wearable scent sensors for recognizing contexts.

## 3. Scent-based context recognition

By recognizing the scent from the dirt of the air, sweat, and food, the wearable system can recognize effective contexts that can be used to provide convenient services in daily life. We employ gas sensors as scent sensors since gas sensors are practically used in various fields and bio sensors are too large to wear in current stage of development. We chose three gas sensors by FIGARO: Air contaminants sensor (TGS2602), Methane sensor (TGS2611), and $CO_2$ sensor (TGS4161). They are low energy consumption, inexpensive, and small enough for wearing. TGS2602 has high sensitivity to hydrogen sulfide, volatile organic compounds (VOCs), and ammonia, for detecting scents such as indoor air contaminants, cigarette smoke, and cooking scents. TGS2611 has high sensitivity to methane, which is used for gas leak alarms in the home. TGS4161 has high sensitivity to $CO_2$ and hardly has sensitivity to other gases. Although $CO_2$ itself is odorless, it can be recognized from user contexts such as indoor population density.

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DOI 10.1109/ISWC.2011.26

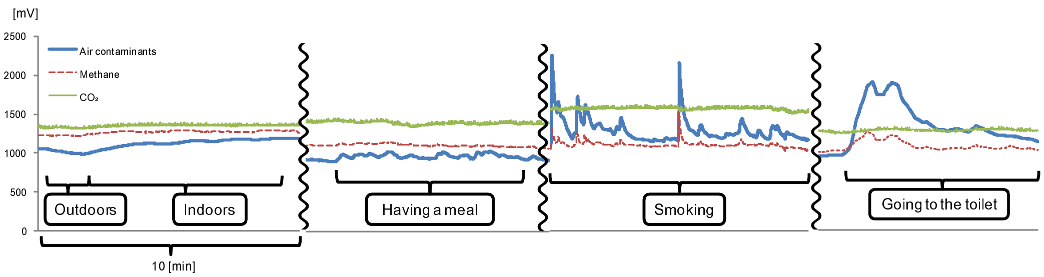


**Figure 1. Example of sensed data**

Figure 1 shows an example of sensed data with these sensors. In the figure, each sensed data decreases gradually when the user goes in the room. In situaltions of having a meal, the sensor readings of air contaminant sensor and methane sensor change quickly. Furthermore, in situations when the person is going to the toilet, air contaminant sensor readings and methane sensor readings suddenly change. In this way, these sensed data show the characteristics for each context. Since these data are not specific and constant data, we need a context recognition algorithm for scent.

## 3.1 Recognition by conventional method

Preliminarily, we evaluated the accuracy of context recognition with conventional feature values to see if the conventional method could be applied to scent based context recognition. Four conventional feature values we are tested in this evaluation: the absolute value, finite difference, average, and variance. For recognizing the contexts, we used five contexts: *being indoors*, *being outdoors*, *having a meal*, *going to the toilet*, and *smoking*. We used the Euclidean distance for calculating the distance between these feature value vectors and all learned vectors. The results shown in Table 1 (sampling frequency 10[Hz], Window Size$=600$) reveal that the absolute value and the average can indicate the contexts of *having a meal*, *going to the toilet*, and *smoking* with a certain level of accuracy. Also, the method combining the average with the variance can recognize these contexts with 0.74 accuracy on average. However, the contexts such as *indoors* and *outdoors* had marked low accuracy since this method uses conventional features and since extracting the characteristics of scent is difficult.

## 3.2 Proposed method

We propose a recognition method that considers the characteristics of the scent sensor. Our method consists of two steps for context recognition as shown in the following.

**Step 1: Classification of contexts into two groups**

The value of scent sensors gradually increases when the user enters a room and drops when the user goes outs, as seen in Figure 1. However, these contexts are easily affected by the environment such as the weather, season and condition of a room and are difficult to be recognized using the conventional feature values because the sensed data of these contexts vary from day to day. Therefore, we classified the contexts of gradually changing the data into group A (*indoors*, *outdoors*), classified the contexts of characteristic data into group B (*having a meal*, *going to the toilet*, and *smoking*), and built a decision tree by J48 algorithm.

**Step 2: Context recognition and detecting continuance**

Subsequently, our method recognizes detailed contexts with the two groups. The value of scent sensors of contexts in group A gradually continue changing after the contexts change. This means that the scent sensor can detect *indoors/outdoors* with the finite difference as the feature value. Our method decides the contexts in group A from three contexts: *indoors*, *outdoors*, or *no change* based on the difference value. The context of *no change* is required because this method cannot detect *indoors/outdoors* directly but can detect the change in location. Concretely, we prepared the method to decide the candidate of the context by comparing the current difference value with the learned data, and if the candidate of the context is *no change*, it is changed to the context of *indoors* or *outdoors* that appears more frequently in last $N$ contexts. In addition, even if the learned data of *indoors* or *outdoors* has the nearest distance, our method detects *no change* when the difference between two successive characteristic values was under the threshold. On the other hand, contexts in group B are recognized using the Euclidean distance with the average and variance as the feature values.

**Table 1. Recognition accuracy vs. features**

| | absolute | difference | average | variance | ave. + var. | ave. + diff. | diff. + var. |
|---|---|---|---|---|---|---|---|
| indoors | 0.55 | 0.31 | 0.52 | 0.39 | 0.54 | 0.54 | 0.39 |
| outdoors | 0.75 | 0.32 | 0.65 | 0.32 | 0.53 | 0.66 | 0.37 |
| having a meal | 0.72 | 0.35 | 0.80 | 0.43 | 0.86 | 0.82 | 0.39 |
| going to the toilet | 0.78 | 0.50 | 0.86 | 0.68 | 0.92 | 0.78 | 0.65 |
| smoking | 0.68 | 0.38 | 0.78 | 0.70 | 0.89 | 0.56 | 0.58 |

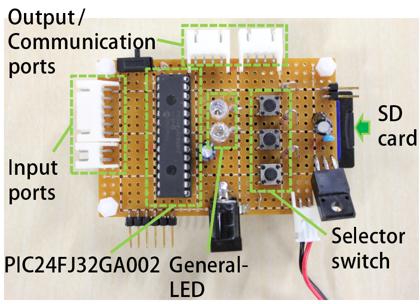


**Figure 2. Prototype of data logger**

| | | | | | | Accuracy | without continuous detection |
|---|---|---|---|---|---|---|---|
| Indoors | 142824 | 14587 | 10018 | 3471 | 4200 | 0.82 | (0.79) |
| Outdoors | 4168 | 37778 | 219 | 418 | 1311 | 0.86 | (0.78) |
| Having a meal | 2013 | 190 | 39213 | 0 | 0 | 0.95 | |
| Going to the toilet | 26 | 54 | 25 | 4490 | 0 | 0.98 | |
| Smoking | 124 | 340 | 66 | 550 | 16491 | 0.94 | |

**Figure 3. Result of contexts recognition**

# 4. Evaluation

## 4.1 Evaluation environment

For the evaluation, we implemented a device logging sensor data, as shown in Figure 2. The data logger has a 16-bit PIC microcomputer PIC24FJ32GA002 of Microchip Technology for input control, and it records the sensor data in an SD card with a sampling frequency of 10[Hz]. The equipped sensors were TGS2602, TGS2611, TGS4161, and three-axis accelerometers MMA7260Q. To evaluate our method, we captured learned data and test data from five different test subjects who wore the scent sensors on their neck and three accelerometers on their waist, foot, and hand. The experimental data were collected over a total of 11 days (March 18 and 19, April 16 and 19, August 4 and 27, September 22 and 24, November 5, December 27, 2010, and January 21, 2011) for all subjects. We randomly selected the learned data in each 20 samples for the five contexts of *indoors*, *outdoors*, *having a meal*, *going to the toilet*, and *smoking* from all experimental data. The remainder was the test data. All data were labeled by hand.

## 4.2 Results of evaluation

For the five contexts, we evaluated the recognition accuracy of our method. The result shows that our method recognized group A with 0.91 accuracy and group B with 0.95 accuracy, which has enough accurate. Then, Figure 3 shows the results in a group $\times$ group confusion matrix. Each cell in the matrix indicates the number of positives per activity (with the true positives diagonally). The figure shows our method had 0.92 accuracy on average. This means that our method achieved higher accuracy than the conventional method using the average and variance as the feature value with 0.74 accuracy. We found that two layered context recognition for the scent sensor was important. Moreover, the context recognition method with detecting continuance for group A had better accuracy on *indoors* and *outdoors* compared with that without continuance detection. This is because the scent was easily affected by the surrounding environment, and sensor values were different in the same situation. The reason for false recognition was not differentiating *indoors* from *outdoors* because of ventilation in the room, smoke being blown away by the wind, and having an odorless meal.

## 4.3 Evaluation of integrative use of scent sensor and accelerometer

In the second evaluation, we showed the effectiveness of the integrative use of scent sensors and accelerometers. In the evaluation, the system recognized three contexts of *walking*, *standing* and *sitting* using three three-axis accelerometers equipped on the waist, foot, and hand, and it recognized detailed contexts combining five contexts from the scent sensors with three contexts from the accelerometers. In the recognition with the accelerometer, the average and the variance of the sensor data we extracted for the feature value, and the recognition accuracy was calculated using Euclidean distance calculation of the normalized characteristic vector and all learned data. We used sampling frequency 10[Hz] for the accelerometer. Figure 4 shows the results of recognizing the detailed context in

| | | | | | | | | | | | Accuracy | only Acc. sensor |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Walking indoors | 17499 | 671 | 277 | 2773 | 275 | 132 | 33 | 22 | 196 | 28 | 0.80 | (0.37) |
| Standing indoors | 965 | 12345 | 374 | 223 | 1255 | 75 | 592 | 0 | 340 | 8 | 0.76 | (0.26) |
| Sitting indoors | 1470 | 947 | 106944 | 358 | 927 | 4669 | 187 | 1043 | 1 | 1375 | 0.92 | (0.40) |
| Walking outdoors | 3116 | 75 | 21 | 32144 | 542 | 15 | 26 | 0 | 34 | 0 | 0.89 | (0.67) |
| Sitting outdoors | 5 | 63 | 0 | 299 | 3743 | 1 | 0 | 0 | 101 | 0 | 0.89 | (0.09) |
| Sitting and having a meal | 22 | 14 | 1774 | 0 | 14 | 34327 | 0 | 0 | 0 | 0 | 0.95 | (0.18) |
| Going to the toilet and standing | 2 | 0 | 0 | 0 | 1 | 0 | 1669 | 3 | 0 | 0 | 0.99 | (0.10) |
| Going to the toilet and sitting | 0 | 0 | 8 | 0 | 0 | 0 | 0 | 948 | 0 | 4 | 0.99 | (0.10) |
| Standing and smoking | 0 | 64 | 0 | 5 | 127 | 0 | 258 | 0 | 7658 | 0 | 0.94 | (0.16) |
| Sitting and smoking | 0 | 0 | 0 | 3 | 8 | 194 | 0 | 0 | 13 | 3118 | 0.93 | (0.27) |

**Figure 4. Contexts recognition on integrative use of scent sensor and accelerometer**

our method as confusion matrix. We did not evaluate the contexts that test subjects did not conduct such as *standing with having a meal*. The integrative use of scent sensors and accelerometers achieved a much higher accuracy than that of the method using only the accelerometers. This is because the use of scent sensors helps to distinguish similar actions but different environmental contexts.

## 5. Application

We implemented a context-aware life-log/QoL-improvement system as an application of our method and the prototype device. Figure 5 shows the GUI of the system. This system acquires the data from a wearable camera, scent sensors, and accelerometers in real-time, and it performs labeling and logging based on our method. In addition, it can protect the privacy of the user by turning off automatically the video recording if it detects the user is *going to the toilet*. Moreover, this system automatically takes a picture when it recognizes that the user is *having a meal*. This system can also be used to improve the quality of a user's daily life. The system warns *"Don't have late-night snacks!"*, *having a meal during irregular hours* or *smoking too much* based on our method. Furthermore, this system advises the user to learn good manners by recognizing the simultaneous contexts of *walking on having a meal*, *walking on smoking*, and *working with bad posture indoors* on integrative use of scent sensors and accelerometers.

## 6. Conclusion

We proposed a context recognition algorithm for scent sensors. Our method considers the characteristics of scent and recognizes contexts such as *having a meal* and *going to the toilet*, which are difficult to be recognized by conventional methods. An evaluation showed that our method

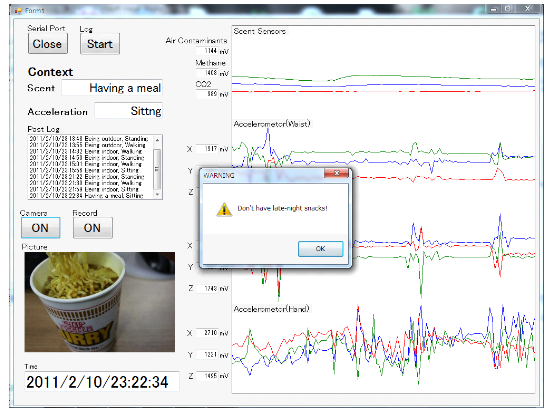


**Figure 5. GUI of the life-log system**

recognized the context of *having a meal* with 95% accuracy and the context of *going to the toilet* with 98% accuracy. Additionally, detailed contexts were recognized by an integrative use of scent sensors and an accelerometer. We introduced context-aware systems that use our method, such as a life-log system for healthcare.

As future work, we plan to design a context recognition method using a different kind of scent sensors to increase the number of recognizable contexts such as ventilating, and to increase the number of test subjects to determine the influence of individual differences.

## Acknowledgment


This research was supported in part by a Grant in aid for PRESTO from Japan Science and Technology Agency and Scientific Research(A)(20240009) from Japanese Ministry of Education, Culture, Sports, Science and Technology.


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