Published in final edited form as:
IEEE Sens Lett. 2017 April ; 1(2): . doi:10.1109/LSENS.2017.2691677.

Investigation of an Indoor Air Quality Sensor for Asthma Management in Children

Utkarshani Jaimini[1], **Tanvi Banerjee**[1], **William Romine**[2], **Krishnaprasad Thirunarayan**[1], **Amit Sheth**[1], and **Maninder Kalra**[3]

[1]Ohio Center of Excellence in Knowledge-Enabled Computing (Kno.e.sis), Wright State University, Dayton, OH 45435 USA

[2]Department of Biological Sciences, Wright State University, Dayton, OH 45435 USA

[3]Dayton Children's Hospital, Dayton, OH 45404 USA

Abstract

Monitoring indoor air quality is critical because Americans spend 93% of their life indoors, and around 6.3 million children suffer from asthma. We want to passively and unobtrusively monitor the asthma patient's environment to detect the presence of two asthma-exacerbating activities: smoking and cooking using the Foobot sensor. We propose a data-driven approach to develop a continuous monitoring-activity detection system aimed at understanding and improving indoor air quality in asthma management. In this study, we were successfully able to detect a high concentration of particulate matter, volatile organic compounds, and carbon dioxide during cooking and smoking activities. We detected 1) smoking with an error rate of 1%; 2) cooking with an error rate of 11%; and 3) obtained an overall 95.7% percent accuracy classification across all events (control, cooking and smoking). Such a system will allow doctors and clinicians to correlate potential asthma symptoms and exacerbation reports from patients with environmental factors without having to personally be present.

Index Terms

Sensor applications; asthma management; cooking; indoor air quality sensor and smoking

I. INTRODUCTION

In a study done by the National Health Interview Survey in 2014, around 6.3 million children in the United States suffer from asthma [1]. Asthma management is challenging as it involves understanding causes and avoiding triggers that are both multi-factorial and unique to each individual. Moreover, it is difficult for doctors to constantly monitor the health of many patients and the environmental triggers simultaneously; or to get adequate data on the environment in which the patient lives. Americans spend 93% of their life

Corresponding author: Utkarshani Jaimini (utkarshani@knoesis.org).

indoors, [2] hence monitoring of the indoor environment of patients is critical for asthma management [3].

To address these challenges, we have developed kHealth[1] (see Fig. 1), a framework for continuous monitoring of patient's personal, public, and population-based health signals that is designed to send alerts to the patient when an adverse condition is detected. The personal-level data includes questionnaires, individualized exhaled nitric oxide level, and indoor environmental measurements as well as activity level measured using fitness trackers.

In this study, we focus on the personal level of the kHealth framework. Specifically, we propose the use of the widely ubiquitous air quality monitor called Foobot[2] to monitor the patients indoor environment. Foobot measures five different air quality parameters (with thresholds defined by Foobot): VOC (300 ppb), PM (25 ug/m3), CO_2 (1300 ppm), Temperature (40 °Celsius), and Relative Humidity (60%). Foobot changes its color from blue to orange if any of the parameters value exceeds their thresholds.

Consider James: an eight-year old boy with controlled asthma recently hospitalized due to multiple asthma attacks. There has been no change in his outdoor environment, lifestyle or medications. The doctors are concerned about these sudden asthma attacks, and their cause? The reason may be the change in the indoor environment, possibly caused by activities such as cooking or smoking (either active or passive), which can lead to increase in PM, VOC, and CO_2. By passive monitoring using Foobot, it is possible to detect these activities and correlate them to James's asthma symptoms. Our research is the first step towards evaluating whether access to data related to patient's living surroundings can help doctors in continuous monitoring of the indoor air quality of their asthma patients and incorporate them with clinical records that contain information on an individual's asthma triggers, allergies, medications, and past emergency room visits for further insights on the role played by the indoor environment in asthma management. The aim of this paper is two-fold: firstly, we present a validation study of Foobot for the measurement of the personal indoor environmental measure in the kHealth framework, and second we present our exploration of whether it is possible to successfully detect cooking and smoking activities in the indoor environment.

II. PURPOSE OF RESEARCH

We compared the indoor air PM level with the outdoor air PM level in Table 1. We observe an elevated indoor PM values as compared to outdoor PM for the environments 4 and 6, which may be caused by conventional cigarette smoking. We also observed a higher indoor PM value in environment 7, which may be due to the cooking activity. For the values of PM and CO_2, a sudden hike is observed during the cooking activity for environment 1 as shown in Fig. 2. Based on these observations, we will address the following research questions:

1. Can we remove redundant Foobot parameters for simplified activity analysis?

[1]kHealth- https://goo.gl/0xlQkn

[2]http://foobot.io/

2. Can we successfully classify the indoor cooking and smoking activities after redundant parameters are removed?

In the next section, we describe the background literature for this study.

III. RELATED WORK

Studies indicate that an increase in the concentration of PM leads to increased emergency room visits of asthma patients [4], [5] and deteriorating lung function in patients with asthma [6]–[8]. Indoor PM concentration varies with different environments and times as a result of various activities such as smoking [9], cooking [10], [11], ventilation [12], and heating [13]. VOC consists of the most toxic chemicals (such as formaldehyde, benzene) which worsens the asthma symptoms and are carcinogenic even at a very low concentration.[3] The VOC reading of the Foobot sensor also accounts for carbon monoxide (CO), if present in the air. The sources of CO inside the house are cooking, conventional cigarette smoking or any kind of incomplete combustion. Cooking produces the largest concentration of PM, four times greater than major haze events in Beijing.[4] Frying, and toasting food with gas or electric appliances produces PM, nitrogen dioxide, CO, CO_2, and VOC. Smoking releases cancer-causing chemicals like CO, cadmium, formaldehyde, and produces up to ten times more pollution than diesel exhaust [14]. The second-hand smoke is known to be a human carcinogenic and can increase the severity of asthma in children [15]. In the following section, we will explore the relationship between these indoor air quality parameters in a data-driven approach.

IV. DATA COLLECTION, ANALYSIS, AND RESULTS

In this section, we discuss our methods and experimental results for the environmental parameters observed using the Foobot which collects data every 5 min. In total, 27 849 data points were collected over 15 days for seven different environments. We collected the data from July to November, 2016 which was late summer and early fall in the areas at different locations within the city of Dayton,Ohio (with zip codes 45324, 45431, 45424, and 45404). The Foobot sensor was placed at an average distance of 10–15 meters from the occurrence of the activities to ensure good match with preferred product operation specifications.

For the analysis, the data points were manually annotated by the user as control, cooking or smoking. The control activity stands for a clean, non-cooking and non-smoking environment. The cooking activity stands for the cooking event (which includes stir frying, deep-frying) using an electric coil-stove, and the smoking activity stands for the presence of conventional cigarette smoking. To test the consistency of the Foobot we conducted two experiments[5] to model 1) the consistency of the Foobot in a controlled environment (without any activity) and 2) the consistency in an environment where cooking activity took place. We computed the Root Mean Square Deviation in both these settings and found the values to be extremely low in the control environment (ranging from 0 to 2.42), indicating that the

[3]http://www.health.state.mn.us/divs/eh/indoorair
[4]http://well.blogs.nytimes.com/2013/07/22/the-kitchen-as-a-pollution-hazard/
[5]https://goo.gl/6MISQs

reliability of the device is high, especially in the controlled environment. The differences in the sensor readings in the uncontrolled (cooking) environment reflect the differences in the PM, VOC, and CO_2 readings in different areas in the room (since we do not see the variation in the controlled environment).

To address the above research questions, we chose environment 1 which had both controlled and cooking data points, environments 4 and 6 for smoking, and environment 7 for cooking. In the subsequent subsections, we will explore the relationship between the Foobot parameters and the activities occurring in different environments.

A. Exploratory Analysis of the Environments

We found high PM, VOC, and CO_2 during the activities of cooking and smoking (see Table 1). We did a Pearson Correlation [16] (see Table 2) to explore the relationship between the five parameters observed by the Foobot sensor. From Table 2, we observe a large positive correlation ($r = 0.72$) of PM with VOC and CO_2. As PM increases or decreases, the concentration of VOC and CO_2 also increases or decreases. During smoking and cooking events we observe an increase in the concentration of PM; VOC and CO_2 also increases as evident in Fig. 2 and Table 1. We also observe a moderate negative relationship ($r = -0.35$) between Temperature and PM. During cold weather, at the time of emission with the decrease in temperature the concentration of PM increases [17]. Humidity is positively correlated ($r = 0.67$) with temperature. As the temperature increases or decreases, humidity also increases or decreases. In this study [18], there is a strong positive correlation between outdoor temperature and indoor humidity. Since most of the data was collected in summer and early fall, it may indicate the use of air conditioning unit. Overall we observe a strong association between the variables PM, VOC and CO_2 (see Table 2). In Tables 1 and 2, the temperature and humidity do not show as much variation as PM, VOC, and CO_2. We want to remove the redundant Foobot parameters. While Pearson correlations tell us about how the variables relate, they do not help us reduce the data. In order to address this, we applied the principal component analysis (PCA) in Table 3 on our correlation matrix to test the independence of the parameters, and reduced the data to two main environmental components, explaining 55.2% of the variation by Component 1 and 31.8% of variation by Component 2 in the data [19].

1. Pollution component (Component 1 which we call Pollution) comprising PM, VOC, and CO_2;
2. Climate component (Component 2which we call Climate) comprising temperature and humidity.

This implies that there are two orthogonal components that describe the indoor air quality using the Foobot sensor. So instead of using the five Foobot parameters in the analysis, we instead use the two principal components. We further test the consistency and reliability of using Foobot with the same activity but in different environments using independent samples t-test at a 95% confidence interval for the mean difference. For the activities control and smoking in the environment group (4, 6) ($13.8 < |t(6793)| < 129.2$, $p \ll 0.001$) and control and cooking in the environment group (1, 7) ($11.8 < |t(9705)| < 189.8$, $p \ll 0.001$), there are significant differences between the groups. An Independent samples t-test provided an evidence that there are significant differences between the control, cooking, and smoking environments.

B. Activity Analysis

We use principal components logistic regression (see Table 4) as a classifier to explore the efficacy of the Foobot parameters in predicting the presence of smoking and cooking in a given environment with the control environment as a reference. The main effects included the Pollution and Climate principal components. In addition, the Pollution-by-Climate interaction was included to account for potential differential effects of pollution caused by indoor climate. We use odds ratios to explain the constant effect of the two components on the activities. Odds ratios for the Pollution component are very large for both the cooking and smoking outcomes, indicating that the probability of detecting a cooking or smoking event increases dramatically with Pollution. Similarly, the odds ratios near zero for the Climate component shows that likelihood of detecting a cooking or smoking event goes down as measures for the Climate component increase. Significant Pollution-by-Climate interactions well above 1 for both the cooking and smoking events (OR = 186.5 and 2.38×10^6, respectively) indicate that Pollution becomes a more powerful predictor of these events as temperature and humidity increase. Using both components and their interaction, we successfully detected the activities of cooking and smoking through an automated system with a total accuracy of 95.7% (see Table V). In Table V, we observe an overlap between the cooking and smoking activity although the diagonal values are higher. The false alarms in the cooking activity are likely due to the confounding factors such as the distance of the Foobot from the cooking area, the lasting effects of cooking and the presence of other activity during that time. These factors are inevitable in patient monitoring, and indicate that more training data are needed to account for these factors. Nonetheless, the classifier gave promising results for the discrimination of cooking (89%) and smoking activities (99%), and is sufficiently accurate to show promise as a useful activity monitor within the kHealth framework.

V. CONCLUSION

Using a principal components multinomial logistic regression classifier, we found that principal components, Pollution and Climate, were able to successfully identify the presence of conventional smoking (with 99% accuracy) and cooking (with 89% accuracy), with a total classification accuracy of 95.7% across all the events (control, cooking, and smoking). The activities cooking and smoking lead to a perceptible change in the environmental parameters PM, VOC, CO_2, temperature, and humidity. The parameters PM, VOC, and CO_2 were better predictors of the activity of smoking and cooking in comparison to temperature and humidity. The use of such a model will help in continuous monitoring of indoor air quality and activity detection within our asthma management framework involving end-to-end validation in a trial of 200 patient cohort. Besides providing more training data for the present classifier, we recommend that future studies build upon this model towards the detection of other PM-inducing events which may exacerbate asthma symptoms such as the use of e-cigarettes, burning incense, sweeping, and the use of particular cooking methods [20].

Acknowledgments

This work was supported in part by the National Institutes of Health under Grant 1 R01 HD087132-01.

The authors would like to thank R. Chandrasekaran and Q. Oliver for their contribution in data collection. The content of this paper is solely the responsibility of the authors and does not necessarily represent the official views of the National Institutes of Health.

References

1. Asthma. Jan. 2017 [Online]. Available: https://www.cdc.gov/nchs/fastats/asthma.htm
2. Klepeis NE, et al. The national human activity pattern survey (NHAPS): A resource for assessing exposure to environmental pollutants. J Exposure Sci. Environ. Epidemiol. 2001; 11(3):231–252.
3. Infante-Rivard C. Childhood asthma and indoor environmental risk factors. Amer. J. Epidemiol. 1993; 137(8):834–844. [PubMed: 8484375]
4. Norris G, YoungPong SN, Koenig JQ, Larson TV, Sheppard L, Stout JW. An association between fine particles and asthma emergency department visits for children in seattle. Environ. Health Perspectives. 1999; 107(6):489–493.
5. Schwartz J, Slater D, Larson TV, Pierson WE, Koenig JO. Particulate air pollution and hospital emergency room. Amer. Rev. Respiratory Dis. 1993; 147:826–831. [PubMed: 8466116]
6. Peters A, Wichmann HE, Tuch T, Heinrich J, Heyder J. Respiratory effects are associated with the number of ultrafine particles. Amer. J. Respiratory Critical Care Med. 1997; 155(4):1376–1383.
7. Dimitrova R, et al. Relationship between particulate matter and childhood asthma–basis of a future warning system for central phoenix. Atmospheric Chem. Phys. 2012; 12(5):2479–2490.
8. Baldacci S, et al. Allergy and asthma: Effects of the exposure to particulate matter and biological allergens. Respiratory Med. 2015; 109(9):1089–1104.
9. Dockery DW, Spengler JD. Personal exposure to respirable particulates and sulfates. J Air Pollution Control Assoc. 1981; 31(2):153–159.
10. Ozkaynak H, Xue J, Spengler J, Wallace L, Pellizzari E, Jenkins P. Personal exposure to airborne particles and metals: Results from the particle team study in riverside, California. J Exposure Anal. Environ. Epidemiol. 1995; 6(1):57–78.
11. Clayton C, et al. Particle total exposure assessment methodology (PTEAM) study: Distributions of aerosol and elemental concentrations in personal, indoor, and outdoor air samples in a southern california community. J Exposure Anal. Environ. Epidemiol. 1992; 3(2):227–250.
12. Sarnat JA, Koutrakis P, Suh HH. Assessing the relationship between personal particulate and gaseous exposures of senior citizens living in Baltimore, MD. J Air Waste Manage. Assoc. 2000; 50(7):1184–1198.
13. Sheldon, L., et al. New York State Energy Res. Develop. Authority. Albany, NY, USA: Tech. Rep.; 1989. An investigation of infiltration and indoor air quality. NYSERDA-90-11 ON: T191001298
14. Medical news today. 2004. [Online]. Available: http://www.medicalnewstoday.com/releases/12481.php
15. Akinbami LJ, Kit BK, Simon AE. Impact of environmental tobacco smoke on children with asthma, united states, 2003–2010. Academic Pediatrics. 2013; 13(6):508–516. [PubMed: 24021528]
16. Primer AP. Quantitative methods in psychology. Psychol. Bulletin. 1992; 112(1):155–159.
17. Rubin JI, Kean AJ, Harley RA, Millet DB, Goldstein AH. Temperature dependence of volatile organic compound evaporative emissions from motor vehicles. J Geophys. Res., Atmospheres. 2006; 111(D3) Art. no. d03305. [Online]. Available: http://dx.doi.org/10.1029/2005JD006458.
18. Nguyen JL, Schwartz J, Dockery DW. The relationship between indoor and outdoor temperature, apparent temperature, relative humidity, and absolute humidity. Indoor Air. 2014; 24(1):103–112. [PubMed: 23710826]
19. Cattell RB. The scree test for the number of factors. Multivariate Behavioral Res. 1966; 1(2):245–276.

20. McCormack MC, et al. Common household activities are associated with elevated particulate matter concentrations in bedrooms of inner-city baltimore pre-school children. Environ. Res. 2008; 106(2):148–155. [Online]. Available: //www.sciencedirect.com/science/article/pii/S0013935107001855. [PubMed: 17927974]

Fig. 1.
kHealth System for Asthma Management using personal, population, and public level signals. Specifically, we examine data from Foobot (is highlighted in green) in this paper.

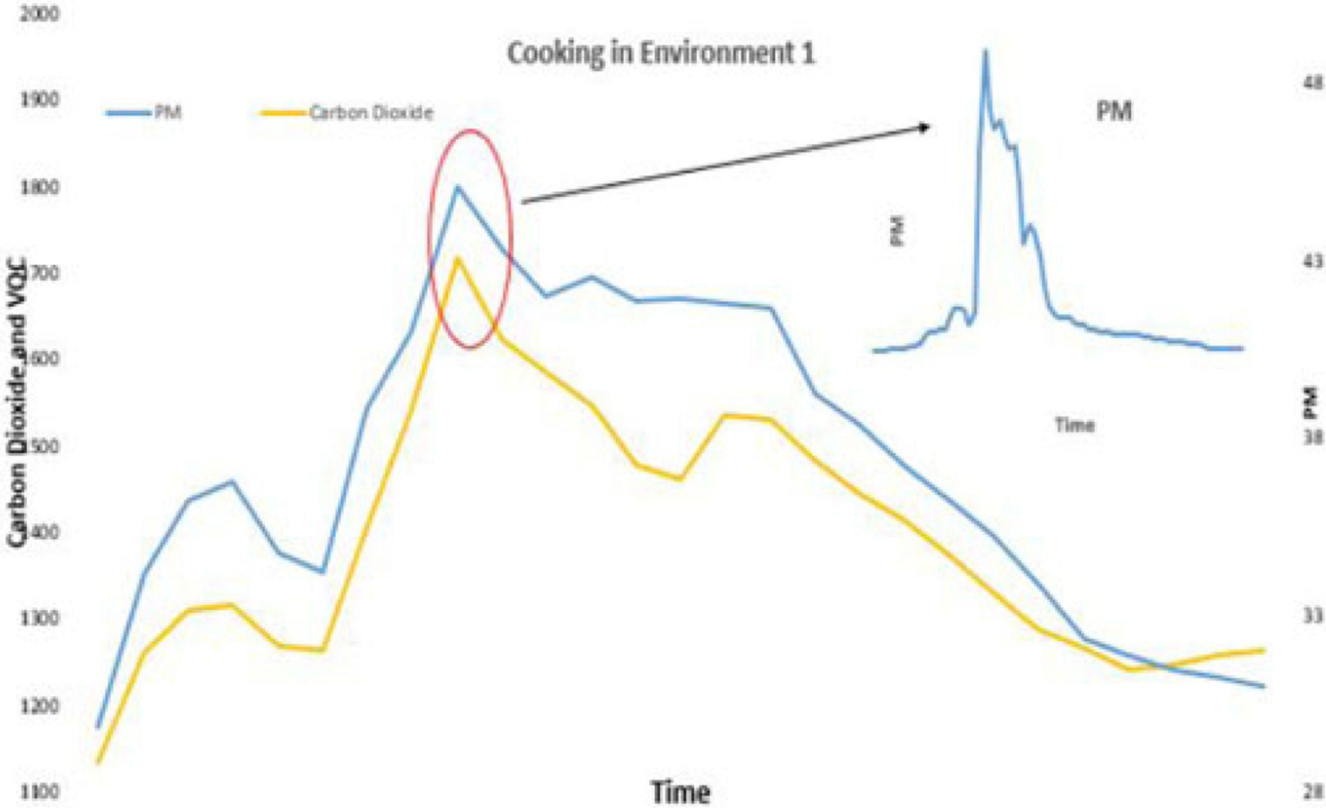

Fig. 2.

Sudden hike in the value of PM and CO_2 due to cooking in the environment 1 with zoomed in hike in PM.

TABLE 1

Sample of Mean and Standard Deviation of the Foobot Parameters in Different Environments

Environment	Outdoor PM	Indoor PM (25 μg/m^3)		VOC (300 ppb)		CO_2 (1300 ppm)		Temperature (40° Celsius)		Humidity (60%)	
		Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
1	38	22.75	15.99	232.34	78.62	839.47	285.54	26.20	1.86	56.16	3.61
4	33.84	59.86	33.17	453.34	230.34	1642.11	836.55	23.73	1.42	59.20	4.36
6	61	78.26	70.58	337.34	78.30	1220.82	653.87	19.26	1.87	44.65	4.96
7	51.5	68.69	90.83	262.29	152.64	948.27	558	19.38	1.67	57.87	4

TABLE 2

Pearson Correlation of Foobot Parameters Across the Environments

	PM	**VOC**	**CO_2**	**Temp**	**Humidity**
PM	1	0.72	0.72	−0.35	−0.19
VOC	0.72	1	0.99	−0.06	−0.12
CO_2	0.72	0.99	1	−0.06	−0.12
Temp	−0.35	−0.06	−0.06	1	0.67
Humidity	−0.19	−0.12	−0.12	0.67	1

Author Manuscript

Author Manuscript

Author Manuscript

TABLE 3

Principal Component Analysis (PCA)

Parameters	Component 1	Component 2
PM	0.88	0.02
VOC	0.93	0.32
Carbon Dioxide	0.93	0.32
Temperature	−0.37	0.85
Humidity	−0.36	0.82

TABLE 4

Multinomial Regression using PCA Components for Cooking and Smoking Environment with Reference to clean (Controlled Environment)

Activity	Intercept(Std. Error.)	χ^2(df = 1)	Odds Ratios
Cooking	19.26 (3.94)	23.81	
Pollution Component	25.03 (4.80)	27.17	7.48×10^{10}
Climate Component	−4.97 (2.01)	6.09	7×10^{-3}
Pollution* Climate Component	5.22 (2.52)	4.30	186.5
Smoking	10.90 (5.04)	4.62	
Pollution Component	41.41 (7.82)	27.98	9.65×10^{17}
Climate Component	−11.51 (2.92)	15.56	9.93×10^{-6}
Pollution* Climate Component	14.68 (4.74)	9.59	2.38×10^{6}

TABLE 5

Confusion Matrix for Multinomial Regression

	Predicted			
Observed	**Control**	**Cooking**	**Smoking**	**% Correct**
Control	98	1	0	99%
Cooking	8	89	3	89%
Smoking	0	1	99	99%
Overall %	35.5%	30.4%	34.1%	95.7%