AFRL-RH-WP-TR-2020-0010

Context-Sensitive System for Particulate Matter

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January 2020

Final Report

for

November 2018 to November 2019

Air Force Research Laboratory

711th Human Performance Wing

711 HPW/RHMO

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REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*	2. REPORT TYPE	3. DATES COVERED *(From – To)*
16-01-2020	Technical Report	Nov 2018 – Nov 2019

4. TITLE AND SUBTITLE
Context-Sensitive System for Particulate Matter

5a. CONTRACT NUMBER
N/A

5b. GRANT NUMBER
N/A

5c. PROGRAM ELEMENT NUMBER
N/A

6. AUTHOR(S)
Thomas Peters, PhD

5d. PROJECT NUMBER
18-095

5e. TASK NUMBER
N/A

5f. WORK UNIT NUMBER
N/A

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
Air Force Research Lab (AFRL)
711th Human Performance Wing
Airman Readiness Optimization Branch
2510 Fifth St., Bldg. 840
Wright-Patterson AFB, OH 45433-7913

8. PERFORMING ORGANIZATION REPORT NUMBER
AFRL-RH-WP-TR-2020-0010

9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)
N/A

10. SPONSORING/MONITOR'S ACRONYM(S)
711 HPW / RHMO

11. SPONSOR/MONITOR'S REPORT NUMBER(S)
n/a

12. DISTRIBUTION / AVAILABILITY STATEMENT
DISTRIBUTION STATEMENT A. Approved for public release. Distribution is unlimited
Cleared, 88PA, Case # 88ABW-2020-0851, 02 Mar 2020

13. SUPPLEMENTARY NOTES

14. ABSTRACT
Aerosol exposure is a major concern in a broad range of military-unique occupational conditions, such as aircraft maintenance and deployments. In this project, we integrated a particulate matter (PM) sensor into a wearable device, the UIowa Personal Monitor, that is able to provide timely, context-sensitive information on the activities that a person experiences. This context awareness functionality was achieved through the use of a custom deep learning model based on a convolutional neural network (CNN). This system is able to predict the current task being performed by using both time and frequency domain features from accelerometery and sound data gathered by a suite of built-in sensors. In parallel with development of the UIowa Personal Monitor hardware, we developed the foundation of our CNN-based task classification model using an existing data set. The data set included continuous, full-shift recordings of upper arm acceleration (triaxial; 20 Hz sampling rate) among eight workers. Overall task classification accuracy was poorest when using only audio data (72.1%) and improved when using only the accelerometer data (85.2%). However, as expected, the combination of accelerometer and audio data yielded the greatest overall task classification accuracy (92.4%, with 5 of 6 task-specific classification accuracies >90%). This system will help workers identify hazardous aerosol exposures, elucidating where the hazards occur during their daily activities. It will automatically link hazardous exposures to specific tasks within the workplace with no or minimal involvement of a health and safety professional.

15. SUBJECT TERMS
aerosols, noise, accelerometry, wearable sensors, personal monitoring, real-time sensing

16. SECURITY CLASSIFICATION OF: U			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
					James Lehman
a. REPORT	b. ABSTRACT	c. THIS PAGE			19b. TELEPHONE NUMBER *(include area code)*
U	U	U	SAR	14	513-558-7462

This report is published in the interest of scientific and technical information exchange, and its publication does not constitute the Government's approval or disapproval of its ideas or findings.

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1.0 Summary

- We have finished prototyping the new Uiowa Personal Monitor.
- We have performed multisensor data collection for model training.
- We have implemented and validated a lightweight convolutional model design for complex task classification on data acquired using the UIowa Personal Monitor.
- We have designed a new package for housing the sensors with the intent to deploy them in the field.

2.0 Introduction

Aerosol exposure is a major concern in a broad range of military-unique occupational conditions, such as aircraft maintenance and deployments. Prolonged aerosol exposure has been shown to cause increased neurological diseases [1-2], cardiopulmonary disease [3-8], and overall mortality rates [9]. The source of an aerosol defines its size distribution and composition, which in turn, play an important role in the health outcome of an exposure. Therefore, the ability to characterize exposure to aerosols in real time, as well as correlate particle concentrations to source attributes (location and activities), is of particular importance when characterizing exposure in dynamic environments. Currently, aerosol photometers are available to measure aerosol concentrations on a time scale consistent with source identification. However, linking concentrations with sources is a time-intensive process, requiring manual interpretation of task diaries or video.

In this project, we sought to integrate a particulate matter (PM) sensor into a wearable device, the UIowa Personal Monitor, that is able to provide timely, context-sensitive information on the activities that a person experiences. This context awareness functionality was achieved through the use of a custom deep learning model based on a convolutional neural network (CNN). This system is able to predict the current task being performed by using both time and frequency domain features from accelerometery and sound data gathered by a suite of built-in sensors.

This system will help workers identify hazardous aerosol exposures, elucidating where the hazards occur during their daily activities. It will automatically link hazardous exposures to specific tasks within the workplace with no or minimal involvement of a health and safety professional. When paired with indicators of health, our new system will enable the epidemiologic study of acute adverse health effects.

3.0 Methods

The objective of the UIowa Personal Monitor design was to create a wearable device that continuously samples and records environmental hazards as well as sampling supplemental data to allow for automated task recognition when encountering potential hazardous environmental situations.

3.1. UIowa Personal Monitor Physical Design Requirements

In integrating the necessary sensors into a wearable, it was important to consider a variety of factors influencing the long-term use of the device. For example, the device had to be lightweight and unobtrusive enough that the worker would not be impeded in their daily activities. The device also had to be laid out in such a way that the sensors are in a good operating location. For instance, the temperature sensor must not be in close contact with the individual's body, where radiant heat might alter the readings, the PM sensor must also be far enough away from the body to allow for unimpeded air flow, and the accelerometer must also be mounted in such a way that it is rigidly fixed to the user and in an appropriate location on the body to detect arm movement associated with performing general tasks. The device must also be capable of operating for a full 8-hour work shift, requiring adequate battery and data storage capability for the whole day. Another factor for the design was that the circuitry must be protected from debris and unintentional impacts as the user works.

3.2. Selection of Sensors

The sensors were selected to monitor and assess common hazards for technicians performing tasks on an air base. It was determined that particle concentrations were appropriate targets to measure due to their correlated negative health impact, and the known presence of small (less than 2.5 micron) particulate matter in aircraft exhaust. After careful review of the available low-cost and low power aerosol sensors, our team selected a dust sensor (Plantower, Model PMS7003, Seul, Korea) capable of detecting particulate matter with an average diameter of less than 2.5 microns (PM2.5). Additionally, this sensor can also measure particle sizes between 0.3-1 micron (PM1), and between 2.5-10 micron (PM10). Hazardous noise levels from jet engines and other machinery were also determined to be an appropriate hazard to monitor. A sound level meter (SLM) was incorporated into this project that was previously developed for use in the Uiowa Personal Monitor system. This custom-built sound level meter was used because we were unable to identify an appropriately packaged noise sensor that could be integrated with the system. In addition to the sound level meter and particulate matter sensors, a temperature and humidity sensor (Adafruit, model HTU21D-F, New York, NY, USA) was included to monitor the heat index of the work environment. Other sensors in this device provided spatiotemporal information for task classification. These include a GPS sensor for rough positional estimation (SparkFun, model ZOE-M8Q, Boulder, CO, USA), an accelerometer to gather body motion data (Adafruit, model ADXL335, New York, NY, USA), and a real-time clock that was built into the main data aggregating device (PJRC, model TEENSY36, Portland, OR, USA).

3.3. Hardware Integration

A redesign of the previously designed UIowa personal Monitoring system was performed to simplify the system, integrate the additional sensors, and to increase the system's modularity. This system replaced the old design's reliance on a smartphone for data aggregation, local storage, and data transfer to a central database with a lightweight Teensy 3.6 (PJRC, model TEENSY36, Portland, OR, USA). The newly designed architecture still utilizes a central aggregating framework that communicates with peripheral sensors, sampling and recording data for particulate matter (PM1.0, PM2.5, and PM10), relative humidity, ambient temperature, relative position, tri-axial accelerometry data, noise levels in A-weighted decibels (dBA), and the raw fast Fourier transform (FFT) data from the SLM, which provides the sound spectral information. In this design, acceleration data are sampled at a rate of 25Hz, while all other sensors are sampled every second. As the data stream enters the aggregator it is time stamped in milliseconds from the start of the recording window, which starts when the device is powered on, and tagged with a sensor ID to link the data to the appropriate sensor. The local data stored on the aggregating device is then transferred to a central database, where a user ID is attached to each datapoint before the data is parsed into searchable subfields. The beginning time of the recording window starting time is labeled using the built-in real time clock and is accurate to the nearest second. This means that the resulting timestamp for each datapoint is precise to the millisecond when referenced to other samples within the recording window but is accurate to the nearest second from the real time clock. This is because the time for each datapoint is the sum of the real time at the beginning of the recording period plus the elapsed time in milliseconds from the start of the recording period.

The general dataflow for this system is shown below, in Figure 1.

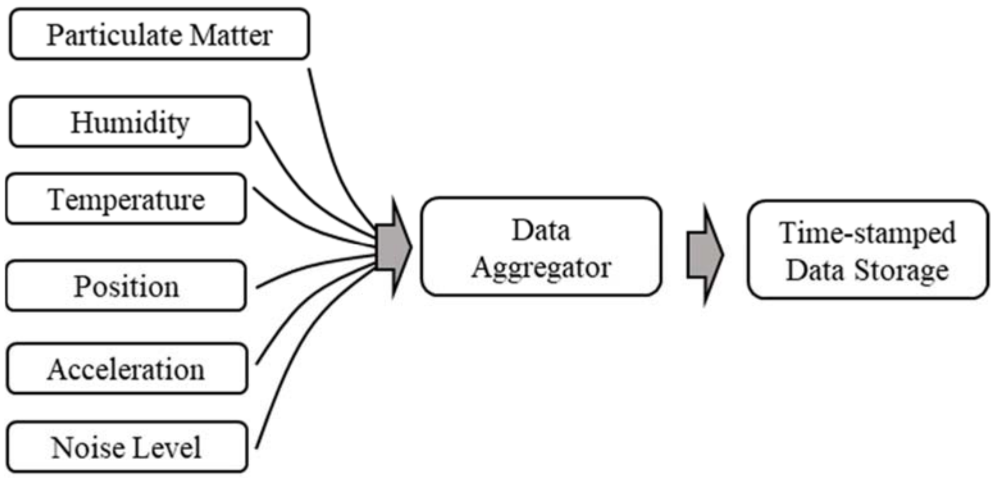

Figure 1: Information flow diagram of the UIowa Personal Monitor system. Environmental information is gathered from the suite of on-board sensors (left) and is fed into the aggregator (center) before being time stamped and saved to local storage (right).

This method of time stamping data points and storing them in a central database enables simultaneous use of multiple monitors. Simultaneous use of monitors allows for tracking of many workers and/or for developing hazard maps in an environment.

An early prototype of this system was developed on a breadboard, shown in Figure 2, and an in-house experiment was designed to simultaneously test the new system and to gather data for the development and testing of the automated task classification algorithm. This system did not have the GPS sensor incorporated due to the lack of position changes for the in-house testing and the fact that our classification algorithm does not yet incorporate this data.

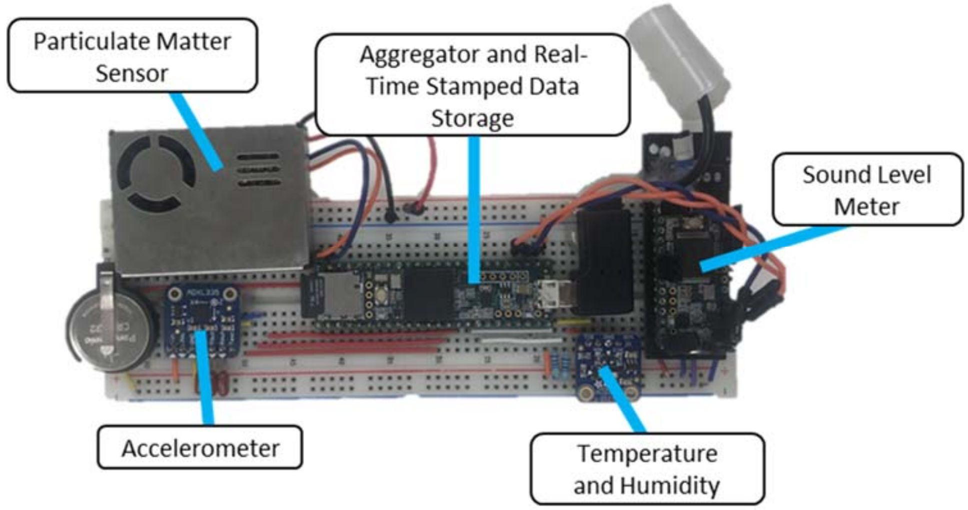

Figure 2: Prototype UIowa Personal Monitor. This system was used for in-house testing of the embedded system performance and for gathering labeled training and testing data for the task classification algorithm. Note, the GPS sensor is not included in this prototype.

The prototype system was mounted to the user's upper dominant arm using athletic tape. The accelerometer was positioned to be just proximal to the elbow.

3.4. Automated Task Classification

We decided that a contemporary machine learning approach (i.e., a deep learning model based on a CNN) would provide an optimal solution for automated task classification. We also considered a fully-supervised approach, in which features of the recorded data we believe important to task classification are identified *a priori* and then rule-based logic is used to automate the task classification process. However, a fully supervised model is not easily modified; for any new tasks we wish to automatically classify in future iterations of the UIowa Personal Monitor, we would first need to predict which features of the recorded data to extract from the raw sensor information. Furthermore, we have elected to use both accelerometer and audio data as inputs to our task classification model. While the combination of data sources increases the information available to automatically classify tasks, it also complicates the process of determining *a priori* which features are relevant to each task and to what extent each feature is linked to the task. A CNN, on the other hand, excels at identifying features of complex data (and the patterns among the features) that best discriminate tasks.

In parallel with development of the UI Personal Monitor hardware, we developed the foundation of our CNN-based task classification model using an existing data set. The data set included continuous, full-shift recordings of upper arm acceleration (triaxial; 20Hz sampling rate) among eight manufacturing workers. Recordings were made for up to 14 consecutive work shifts while rotated among 10 distinct manufacturing workstations (i.e., tasks). The time at each task was also recorded using radio frequency identification, which provided the "labels" assigning a task each triaxial accelerometer sample. Advantages of existing data set relative to the current project were the availability of accelerometer data from the upper arm (the proposed mounting location of the UI Personal Monitor), labels for complex tasks performed for varying durations, and repeated observations of tasks both within and between subjects.

Although the existing dataset did not contain audio data, it allowed us to evaluate the efficacy of different CNN-based task classification model designs. We built, trained, and tuned a variety of models. In general, the use of successive depthwise 1D convolutional layers on the input acceleration channels prior to applying a series of normal 1D convolutional and maxpooling layers led to the greatest task classification accuracy with the fewest parameters.

With the underlying architecture identified, and once the UI Personal Monitor had been developed to a prototype state that could be mounted to the upper arm, we worked to incorporate audio information with accelerometer information for the purpose of automatic task classification. Specifically, we developed a set of representative tasks that (i) airmen might perform in the field and (ii) generate accelerometer and audio data signatures that when used in combination might provide better task classification accuracy than either data source alone. The experimental tasks were as follows:

1. Tasks with similar upper arm acceleration profiles but different sound profiles:
    a. Driving 30 fasteners using a standard, direct-drive electric drill/driver
    b. Driving 30 fasteners using an electric impact driver
2. Tasks with different upper arm acceleration and sound profiles:
    a. Driving 30 nails using a manual hammer
    b. Driving 30 nails using a pnuematic nail gun
3. Tasks with similar sound profiles but different upper arm acceleration profiles:
    a. Moving the nozzle of a vacuum back and forth slowly (controlled by metronome)
    b. Moving the nozzle of a vacuum back and forth quickly (controlled by metronome)

Seven individuals each performed three trials of each of the six tasks listed above. The architecture of the CNN-based task classification model (developed using the existing data set, as described above) was then modified to accept both accelerometer and audio data as inputs. The raw sensor signals were pre-processed prior to entry into the CNN due to variation in both sampling rate (i.e., 25Hz for accelerometer and 1Hz for audio) and dimensionality. Specifically, raw signals were parsed into non-overlapping epochs of three seconds in duration and then identified global maxima within each epoch for both the accelerometer and the audio FFT data. While this approach will not be immediately generalizable to louder environments or more complex tasks, it does allow for a substantial decrease in data dimensionality. We developed CNN model training and testing sets based on the 3-second epochs across all subjects and trials (i.e., ‘between-epoch’ evaluation). 80% of all 6-second epochs recorded were randomly assigned to the training set and the remaining 20% assigned to the testing set. From the testing set, the overall task classification accuracy was then calculated as the proportion of epochs for which the model correctly predicted the underlying task.

To examine the effect of using both audio and accelerometer data together for task classification, we also designed the model to optionally ignore the accelerometer or audio data. In this way, we were able to examine task classification accuracy for three model configurations: one that included only accelerometer data, one that included only audio data, and one that included both accelerometer and audio data.

3.5. Development of Fully Deployable Device

With the remaining time in the project we began working on developing a fully deployable version of the new UIowa Personal Monitoring system. Work was done to re-package the sensors using in this device into a wearable that can withstand field conditions, offers a better sensor distribution for more accurate readings, and . Consideration was also taken in designing a comfortable device that could be worn for long periods of time, with an 8-hour workday being the primary goal. Figure 3 shows a user wearing a prototype of the UIowa Personal Monitor system.

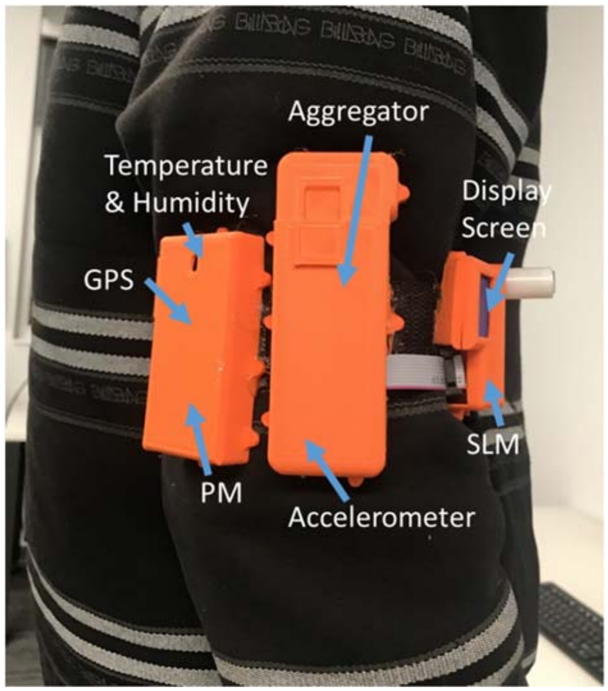

Figure 3: Ruggedized UIowa Personal Monitor worn on the right arm. Blue arrows point to the corresponding sensor and display location within plastic housings attached to an arm band.

4.0 Results and Discussion

4.1. Automated Task Classification Results

Tables 1-3 include the task classification accuracy results for the models including the accelerometer data only (Table 1), audio data only (Table 2), and both accelerometer and audio data (Table 3). Overall task classification accuracy was poorest when using only audio data (72.1%), which appeared driven largely by substantial confusion between the slow vacuuming (Task 3A) and fast vacuuming (Task 3B) conditions (9.7% accuracy in classifying these two tasks based on audio alone). Overall task classification accuracy improved somewhat when using only the accelerometer data (85.2%). However, as expected, the combination of accelerometer and audio data yielded the greatest overall task classification accuracy (92.4%, with 5 of 6 task-specific classification accuracies >90%).

Table 1: Task classification accuracy using only accelerometer data.

		Predicted task (n)						Accuracy, by
	Task[1]	1A	1B	2A	2B	3A	3B	task[2] (%)
True task (n)	1A	124	10	4	0	0	0	89.9
	1B	46	79	0	1	1	0	62.2
	2A	7	3	200	3	0	0	93.9
	2B	6	0	2	39	0	1	81.3
	3A	1	1	0	0	114	6	93.4
	3B	1	2	0	0	9	39	76.5
		Overall task classification accuracy[3] (%)						85.2

[1]As listed in Section 3.4
[2]Within-row, count in shaded cell as proportion of total count
[3]Sum of counts in all shaded cells as a proportion of total counts across all rows

Table 2: Task classification accuracy using only audio data.

		Predicted task (n)						Accuracy, by
	Task[1]	1A	1B	2A	2B	3A	3B	task[2] (%)
True task (n)	1A	101	21	8	2	6	0	73.2
	1B	7	117	23	2	2	1	77.0
	2A	5	24	149	2	6	1	79.7
	2B	4	8	5	22	2	0	53.7
	3A	0	1	4	0	108	6	90.8
	3B	0	3	8	0	45	6	9.7
		Overall task classification accuracy[3] (%)						72.1

[1]As listed in Section 3.4
[2]Within-row, count in shaded cell as proportion of total count
[3]Sum of counts in all shaded cells as a proportion of total counts across all rows

Table 3: Task classification accuracy using both accelerometer and audio data.

		Predicted task (n)						Accuracy, by
	Task[1]	1A	1B	2A	2B	3A	3B	task[2] (%)
True task (n)	1A	121	8	2	2	0	0	91.0
	1B	8	130	0	3	1	0	91.5
	2A	0	2	199	1	2	1	97.1
	2B	0	0	0	36	0	0	100.0
	3A	1	0	0	1	117	7	92.9
	3B	0	1	1	0	3	42	89.4
		Overall task classification accuracy[3] (%)						92.4

[1]As listed in Section 3.4
[2]Within-row, count in shaded cell as proportion of total count
[3]Sum of counts in all shaded cells as a proportion of total counts across all rows

4.0 Conclusions

We successfully developed a functional embedded system with an appropriate sensor suite for detecting and logging environmental hazards that might be experienced by an airman working on base. We completed prototyping of the hardware and embedded system.

We designed, trained, and tested a prototype neural network that is capable of classifying a set of six different work tasks. These tasks were selected with the intent to test the importance of audio and acceleration data on model prediction accuracy. We have shown that using the two input data streams does increase the model accuracy over a system which only analyzes one of the two data types. We have also successfully shown that the model can produce high levels of accuracy with relatively few parameters when attempting to classify highly complex tasks, providing the foundation for a robust, easily trained model for task recognition. This finding is promising given the comparatively small sample of data that we have gathered for training this model. We would only expect improved accuracy as we gain more data during future trials. Because we decided to use a machine learning approach, this also means that our model is expected to be highly adaptable and we can re-train it with new data for additional tasks that might be encountered in the field without the need for expert analysis and generation of a completely new algorithm.

This work has the potential to positively affect technicians in the field by bringing them a new level of understanding for the potential hazardous environments that they may encounter. It will also reduce the burden of human processing in identifying potential existing or new hazards in the workplace by automatically recognizing tasks that the user is performing and relating those tasks to potentially hazardous levels of particulate matter, or damaging sound levels that might occur during these tasks.

Future work will include the development of a fully deployable version of the UIowa personal monitoring system. We will use this version of the monitor in field tests to enable classification of tasks directly relevant to the Air Force. We will also implement software features to make the monitoring system more user-friendly.

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