SousTech: Automatic Food Classification

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Image-based food recognition has developed recently as the result of more effective deep learning techniques, and the widespread availability of image capturing devices[1]. However, there is little research available on classification of food items via gaseous emission. Similar to how humans recognize food based off of its smell, we propose a device that uses the presence of various gasses during the cooking process in order to classify the food being prepared. This system, called SousTech, may be used to supplement existing food monitoring systems for both home use and automatic diet monitoring frameworks.

1 Introduction

1.1 Motivation

Automatic food and diet monitoring are a tool to aid those for whom food consumption is regulated in order to prevent illness or health complications. Especially for diabetes patients, the active monitoring of glucose intake is difficult for a human to manage, and even harder for computers to keep track of. Furthermore, according to a study performed by the National Center for Health Statistics in 2015, nearly one-third of all US adults are obese[2]. Although diet monitoring is less crucial for the men and women who suffer this, having a system in place that could aid them in making healthier decisions might lead to an improved quality of life.

Finally, a food monitoring system can also be used as an aid in safe food preparation. Examples of this include ensuring that meat is cooked thoroughly, that all food is being monitored consistently, and that nothing is burning or at risk of causing a fire. While we will not consider these applications, the project was designed with them in mind as well.

1.2 Solution

In order to address the difficulties of food monitoring, we designed a self contained sensor apparatus called SousTech that can act as a digital ”nose” for a stovetop environment. By attaching to the underside of stove hood, SousTech can monitor the gasses being released by food items as they are cooking in order to determine what is being prepared. We designed it to be low cost and easy to install so that it can blend into the kitchen and passively monitor all stove top activity.

1.3 Prior Work

Although ”Electronic-Nose”s such as the one we have proposed have been used over the past 40 years, there do not exist any general platforms or hardware that can precisely track

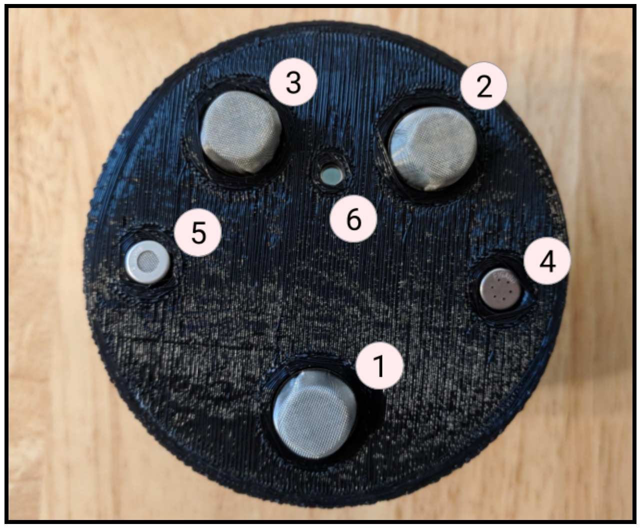

Figure 1: SousTech Sensor Apparatus, Underside, Sensors Labeled

a wide variety of gases and aromatic emissions. Furthermore, that great majority of such research has been for use in industrial settings[3]. Even with regard to food monitoring via electronic-noses, most work is limited to monitoring freshness or suitability for consumption. As such, there is little research into the practicality of these sensors for home and consumer use[3].

1.4 Contribution

SousTech provides a convenient, cheap, and portable system for monitoring food gas emissions within the home. Furthermore, we have shown that it is capable of classifying an array of both similar and dissimilar food items based solely off of its included sensor apparatuses. Finally, it suggests that automatic diet monitoring systems can be augmented with gas detection sensors in order to provide more nuanced information to the users of the system.

Name	Label	Primary Reactant
MQ-4	1	Methane Gas (CH_4)
MQ-6	2	Liquefied Petroleum Gas (LPG)
MQ-8	3	Hydrogen Gas (H_2)
TGS2620	4	Alcohol Gas
TGS2602	5	Volatile Organic Compounds (VOC)
MLX90614BAA	6	[Infrared Thermometer]

Figure 2: The Sensors used in SousTech

2 SousTech

The SousTech prototype is a sensor array that can attach to the underside of a stove hood. Initially, it contained only the 5 gas sensors being used for classification. However, early tests revealed that using raw sensor data was unexpectedly noisy as a result of the temperature change over time. Since each of the sensors use heated elements to initiate the chemical reactions that result in the data output, the increased temperature from the stove top caused unwanted fluctuation in the sensor output. To this end, a second version — shown in Figure 1 — was designed that included both an external infrared thermometer and an internal contact thermometer. Thus the final device had a total of 7 sensors in 6 discrete components. Each of these sensors were publicly available at a cost between \$5 and \$10 at the time of construction with the exception of the thermometer, which was situated at roughly \$15. Figure 2 lists each sensor and what it does.

In addition to the 6 sensors, the chassis also houses an Arduino that polls the sensors and transmits data to a host computer over serial. The chassis itself is 3D printed and contains a lid with a cyclic locking mechanism to hold it in place. This allows us to embed a magnet into the lid that can then support the full weight of the device, allowing it to remain fixed on the hood while simultaneously easily modified and repaired. This is shown in Figure 3.

Since the Arduino itself does not have sufficient persistence to store the data as it is recorded, all data is immediately transferred to a computer which is then responsible for any storage, analysis, or classification. A simple command line interface (CLI) shown in Figure 4 handles

Figure 3: SousTech Sensor Apparatus, Top Side

communication and storage, as well as using the computer's microphone to enable voice annotations during data collection. Furthermore, this interface can be used to examine the state of the sensors, either at the current moment, or over the past 30 seconds. Finally, the script has compatibility for exporting data to WEKA's[4] ARFF format, and importing generated trees in order to perform real-time classification.

3 Acquisition and Analysis

3.1 Data Collection

The robustness of the device and the broad functionality of the corresponding CLI allowed us to focus on the data. Once the final prototype had been completed, individual data samples were collected in intervals of 20 minutes. Initially, the device would be placed on the stove hood at a distance of approximately 0.75 meters from the burner. Then, we would preheat the burner to 160 degrees as measured by the infrared thermometer (note that because of wide FOV on the sensor, this is not the same as heating the burner to 160 degrees) and place a pan atop it. Once the burner had come to temperature, we would choose a food item to sample, and place it on the pan for as long as necessary to "cook" it. Although we remained consistent in our duration among food classes, we would necessarily need to vary it

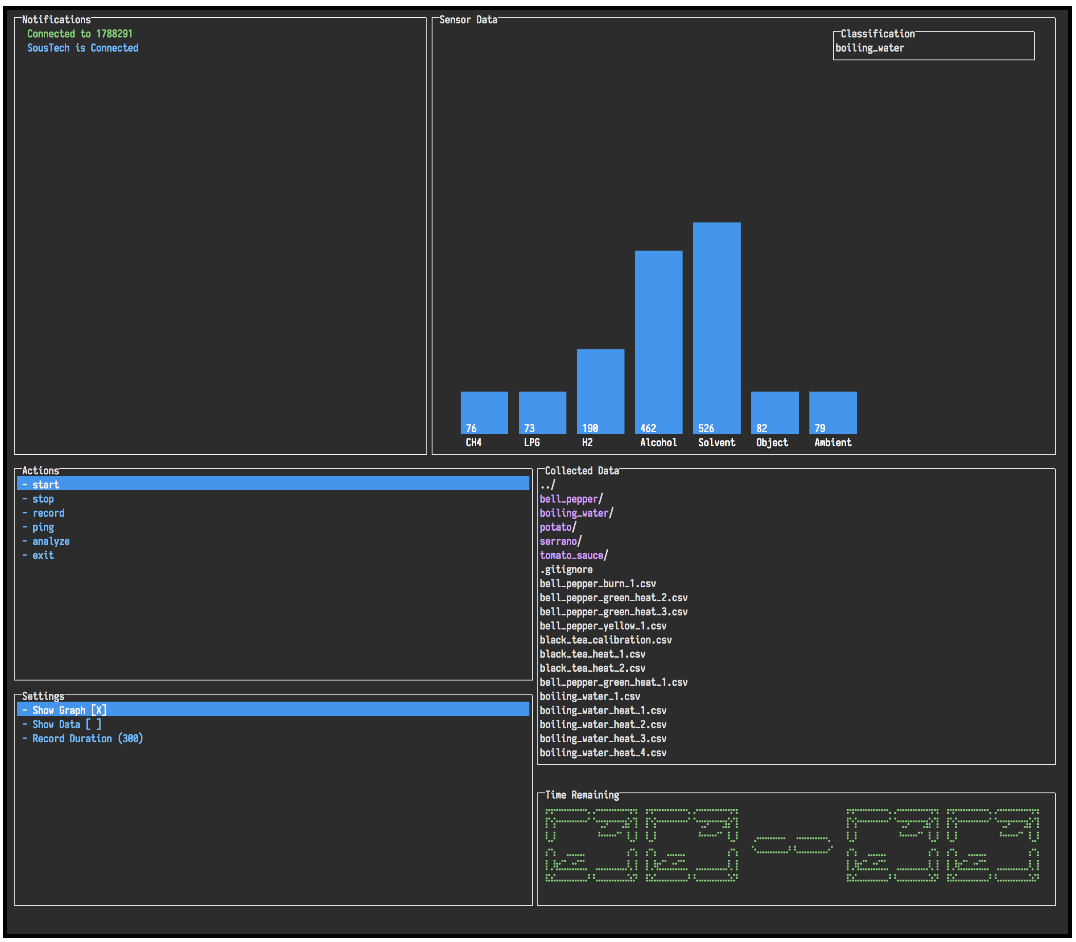

Figure 4: Command Line Data Capture Interface

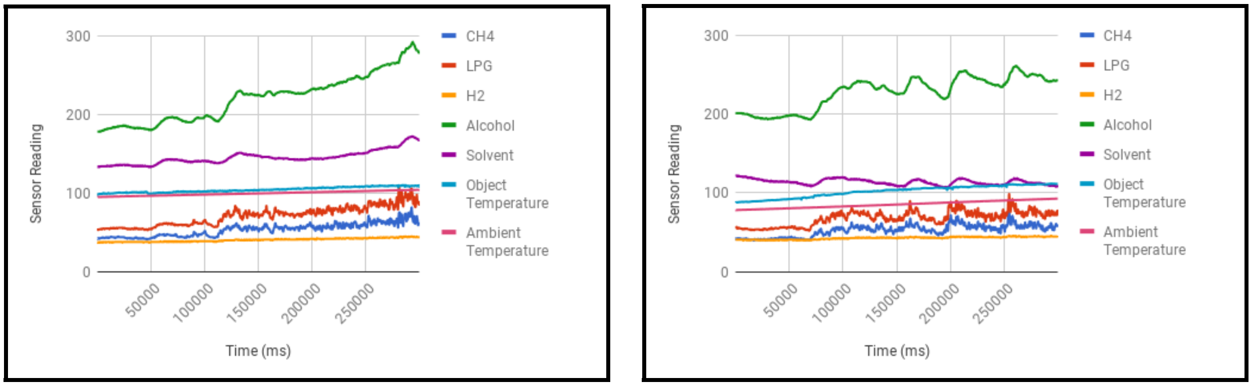

Figure 5: Two Different Samples of Tomato Sauce over 5 Minutes

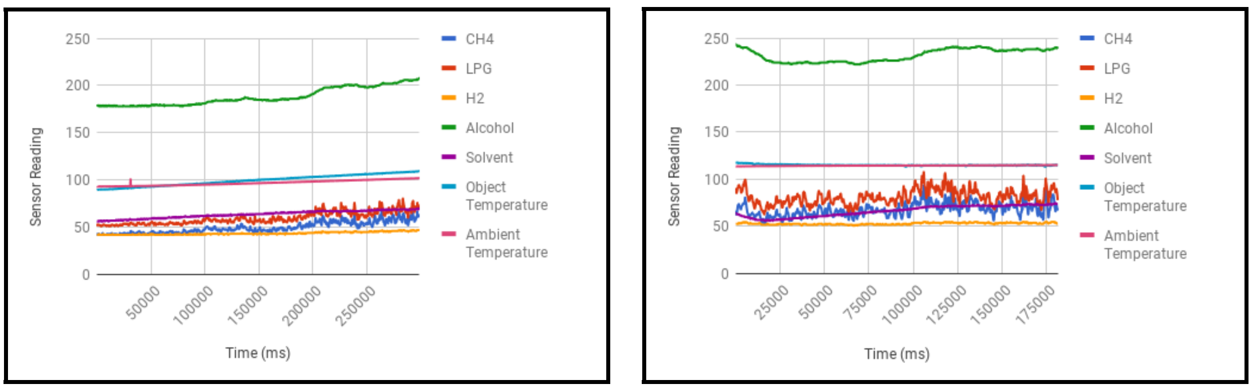

Figure 6: A Sample of Boiling Water (Left) and Black Tea (Right)

between them. In most cases, however, this would be around 5 minutes a sample. Once the measurement was complete, we turned off the burner, removed the device from the hood, and gave everything 15 minutes to cool down, at which point we could begin again.

Using this method, we took approximately 100 minutes of data among 6 classes: **Potato, Boiling Water, Black Tea, Tomato Sauce, Bell Pepper,** and **Serrano Pepper**.

3.2 Data Analysis

Initially, the data suggested that we might not be able to derive a signal as we had hoped. Consider Figure 5, which shows two different samples for the same food item (in this case tomato sauce). Visual inspection suggests that the two are wildly different, and does not indicate any obvious correlation. Furthermore, there seemed to be high degrees of similarity between different classes. Figure 6 shows two different classes that have comparably similar emissions. Although it seemed that this data would be unusable, we tested this concretely by performing a point-wise classification on each of the samples. Although this discards the context of change over time, preliminary analysis showed that it is effective in classifying the item, despite earlier fears.

As mentioned earlier, the SousTech software had a method for outputting Attribute-Relation File-Format (ARFF) files that could be imported directly into the WEKA[4] data analysis software. Once the data was imported into WEKA, we used 5-fold cross validation to determine how well correlated the data was. Cross validation was selected for this as it allowed us to make use of all available data in evaluating the model, while simultaneously ensuring that no individual set of samples varied too greatly from the remainder. Since the analysis at this point is preliminary, we opted for a simple model of classification, a random forest.

Using this technique, the random forest classifier was able to achieve an accuracy of greater than 99.9%. Specifically, out of the 24,000 samples provided to WEKA, only 7 were misclassified. Furthermore, the model has a κ-statistic of 0.9996. This indicates that the random forest provided an exceptional model for the collected data. However, although we initially wanted to use a random forest for classification, for the purposes of real-time classification, we determined that a single tree would serve as a more effective classifier due to its simplicity and portability. Using this model, we had a minor increase in mis-classifications, up from 7 to 30, with a new κ statistic of 0.9985. With this new model, now we were able to perform real time classification. Although we have not yet collected substantial data using this real time classification, we observed that in every sample tested, (one from each class), there was a stretch of at least 2 minutes over which the classifier performed perfectly.

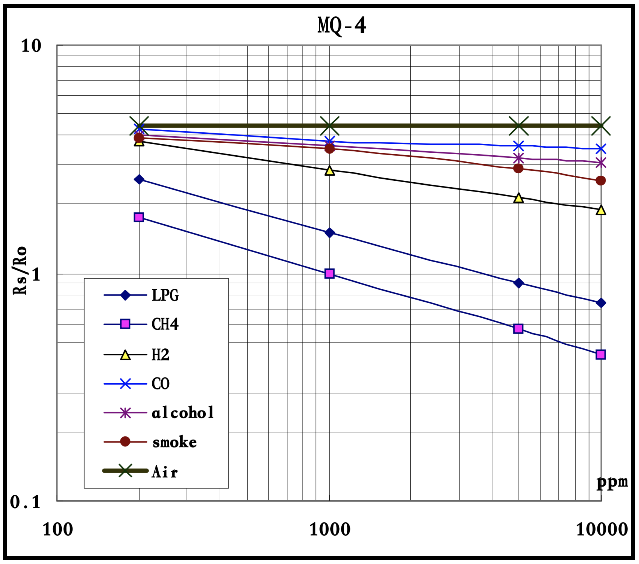

Figure 7: Gas Response Curves, MQ-4[5]

3.3 Concerns

As mentioned previously, the gas sensors we used were off-the-shelf and cheap. As a result, none of them respond to a singular compound. Consider Figure 7, taken from the MQ-4 datasheet [5]. Although it is evident that the sensor responds most strongly to CH_4, there is a significant overlap with LPG, H_2, and even smoke. As a result, it masks the actual signal, and makes it less clear to what the sensors are responding. Furthermore, with the size of data collected thus far, it is unclear whether, for instance, external environmental effects could be clouding the classification of these food items.

4 Lessons

The research performed here is unique in its consumer facing approach. Although these sensors in general have uses in manufacturing and industrial management, there is little data on how they could be harnessed for daily life. As such, when approaching this problem it was unclear whether we would be able to find any signal among the noise. For these reasons, although the data is preliminary and needs a wider variety of environments and input data, the results we have so far are very encouraging. The greatest surprise of this project was that it worked at all. Furthermore, we now have a greater understanding of which sensors are most useful in classifying food, and which are effectively redundant. Throughout this process, we also learned a great deal about designing effective stove top hardware. Unlike in other applications, when electronics are placed in locations with large thermal fluctuations and where a hardware failure could lead to fires or burns, they need to be incredibly sturdy and secure. This led us to designing an improved ventilation system, a jostle-resistant locking mechanism, and an overall small and portable chassis.

5 Summary

5.1 Further Work

Although we made great progress in using an electronic nose to classify individual food items during preparation, there are still many ways this research could be expanded upon. The first, and most important, is to scale the current research up to more food items, as well as composite items. It is unclear at this point whether the sensors can detect when multiple ingredients are combined. Furthermore, although we observed a strong signal for "stirring" and "burning," we have not yet quantified this or determined how precisely the device can detect these actions. Pursuing this further would allow us to determine in what other ways we can use this technology to improve the lives of common consumers. There are also several avenues for expanding the hardware backing SousTech, including adding microphones, cameras, or spectroscopic sensors to the devices. Finally, we would like to see how well this technology could be miniaturized and embedded into wearable platforms.

5.2 Conclusion

We have constructed a small sensor apparatus that can be affixed to the top of one's stove and then examine the levels of various gases being emitted from food items cooked beneath it. Furthermore, we have shown that it is possible to classify foods as they are being cooked using these gaseous emissions. Even in cases where the food items are similar — such as between bell peppers and serrano peppers or between boiling water and black tea — this ”electronic nose” based approach was still able to distinguish them. Thus, this approach is suitable for tracking and classifying food during its preparation, and could be used to improve automatic diet monitoring systems, as well as home appliances in general.

References

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A Code

All code for this project is available at http://github.com/zwade/SousTechInterface. Reproduced below is the readme.

A.1 SousTechInterface

This repository is used for managing and working with SousTech hardware.

A.1.1 Setup

Please run `npm install` before attempting to use and of the files in this repository. This is untested on all platforms except for OSX 10.12. Even then, use this at your own risk.

A.1.2 Capture

The program capture.js is the main program of this project. Once the SousTech prototype has been plugged in, running `./capture.js` will launch a Blessed interface that contains options for interfacing with the prototype.

To get started select start from the Actions menu. This will instruct the device to begin transmitting data. From there, you may begin recording by selecting record, ping the device by selecting ping, or see a full screen line chart by hitting space. In addition, if you would like to see the data as it is coming in, you may select Show Data from options.

A.1.3 ARFF Generator

In order to run the data through WEKA, you need to generate an ARFF file for it. The `prepareData.js` script will do this, although it expects the data to be organized in folders within the data directory. Once you have done this, update the classes array to contain these folders and run the script. The output will be located in `/training/training.arff`.

A.1.4 Live Classification

For live classification, run use the `prepareData.js` script to generate a WEKA compatible file, then use a Randomized Tree Classifier to generate a model. Once the model has been created, copy the resulting tree into `weka.tree`. The next time you run `./capture.js`, `wekaParse.js` will translate the tree into JavaScript, and then load it.

B Hardware

The `.stl` files are available for the hardware here: https://github.com/zwade/SousTechInterface/releases.