Non-contact Medium-based Respiratory Analysis through Reinforced Hybrid Model

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***Abstract*—The ability to monitor natural respiratory behaviors is essential to pulmonology. Existing contact-based respiratory monitoring methods are known for their accuracy, but are generally considered uncomfortable, whereas non-contact methods are comfortable but less accurate. Thin Medium Thermal Imaging (TMTI), a respiration monitoring method that uses a thin medium and thermal imaging to sense breathing activity, was proposed as an alternative non-contact method that monitors respiration directly. However, the accuracy of this method suffered due to lack of information about airflow behaviors occurring between the user's mouth and the medium. In this paper, we describe a reinforced hybrid model that utilizes a thermal camera with a spectral filter (3-5[μm]) to provide breathing behavior information in addition to a low-cost thermal camera to capture images of the medium. The thermal camera with a spectral filter visualizes CO_2, giving us the ability to observe the turbulent behavior of exhaled airflows. By further understanding the relationship between human breathing behaviors and the heat signatures on the medium using this hybrid model, we are able to classify breathing mode with at least 91% accuracy.**

I. Introduction

Pulmonologists employ a variety of respiratory monitoring tools to accurately assess the health of a patient, such as spirometers, plethysmographs [1], and polysomnography [2] [3]. Termed "contact methods", these techniques require placing sensors directly on the body of the patient. Though these methods boast high accuracy and utility, these methods often inflict physical and psychological discomfort, and interfere with a patient's natural breathing behaviors [4] [5]. The most invasive techniques can only be used for short durations, yet they provide information that cannot be obtained through other methods. Additionally, cumbersome equipment and labor-intensive setups make these techniques difficult to utilize in out-patient clinics. Proposed non-contact measurement methods using remote sensors such as thermal cameras [6] [7] [8], RGB cameras [9] [10], depth sensors [11], ultrasonic sensors [12], and RF devices [13] [14] [15] [16] [17], though comfortable, are not currently used due to their lowered accuracy, sensitivity to bodily characteristics, and limited utility. Thermal imaging methods that monitor breathing in open air [6] have reduced accuracy due to fast heat dissipation, and methods that measure skin temperature changes [7] [8] are unable to provide detailed breathing behavior information.

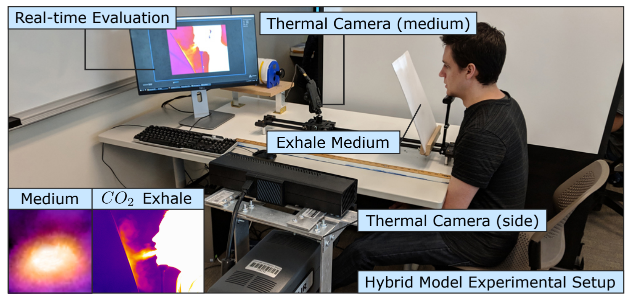

Fig. 1: Experimental setup for thin-medium [18] and exhaled CO_2 breathing monitoring [19] for respiratory analysis.

Thin Medium Thermal Imaging (TMTI) is an innovative non-contact respiration sensing method that strives to address the problems of existing methods by monitoring respiration directly, but without touching the patient [18]. In this method, a patient breathes onto a thin medium while a thermal camera records images of the opposite side of the medium as shown in Figure 1. The thin medium accurately captures the heat signature of the breath, retaining the temperature gradient long enough to be recorded by a thermal camera, but dissipating the heat quickly between breaths. Processing these images using signal processing or machine learning converts the thermal signatures on the medium into clinically important metrics such as respiratory rate and volume, and provides additional breathing behavior information to clinicians for a comprehensive view of the respiratory functioning of a patient [18] [20] [21]. This method requires small, low-cost equipment, and works for a variety of patient populations.

Though this method provides a variety of respiratory metrics and behavior information, previous papers use estimated values and self-reported information from the subject to fill in the gaps of unseen activity behind the medium. Metrics such as the distance between the person's face and the medium, the delay between the start of a breath and when it hits the medium, and the person's breathing mode (whether the person is breathing through their nose, mouth or both) are unknown. Data taken by having a person breathe through a spirometer onto the medium can provide accurate timing and exhale information, but the resulting heat signatures do not represent natural breathing. Without a ground-truth device, the onus of following instructions to breathe in a specific way

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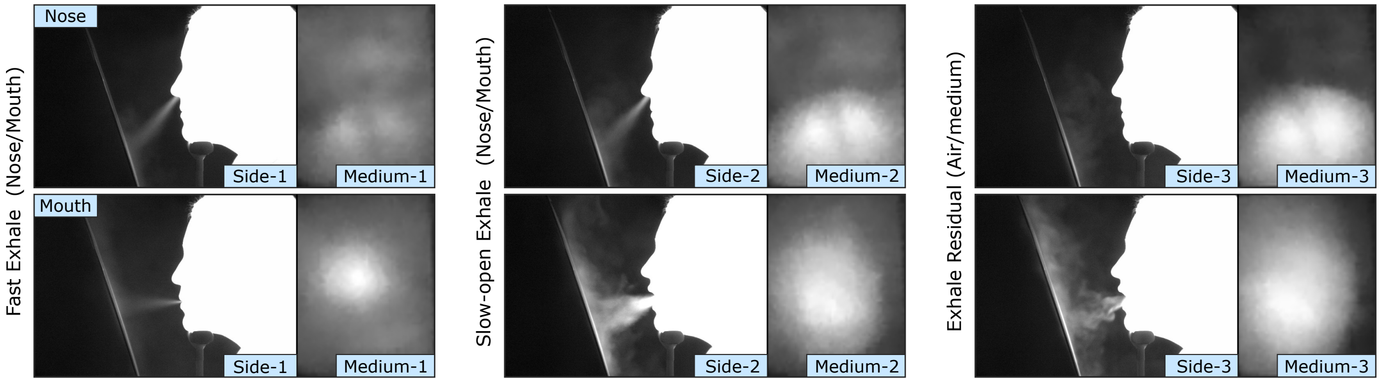

Fig. 2: A thermal exhale sequence showing images from the medium-view and the side-view.

and maintain a constant distance from the medium during data collection falls to the test subject. Removing uncertainty about what is going on behind the medium is necessary to improve this method of respiratory monitoring.

In this paper, we employ a reinforced hybrid breathing model that uses an additional thermal camera with a spectral filter in the 3-5[μm] range. This camera acts as a CO_2 particle sensor, visualizing turbulent airflows as they exit a person's mouth or nose and collide with the medium. By collecting images from this camera from a side-profile while also collecting thermal images of the medium, we are able to see the human and airflow behaviors that contribute to the thermal signatures on the medium. These synchronized image sets are used to train a Convolutional Neural Network (CNN) to identify breathing activities from medium images from an inexpensive device.

II. Method

The premise of our method is to provide a data-driven correlation between exhale behaviors on a thin medium with the actual CO_2 exhale of the user. The purpose of this model is to improve the accuracy of data extracted from using medium-view images collected from a mobile thermal camera. We use the medium-view images and data extracted from the CO_2 camera images to train a CNN model that correlates breathing behaviors with thin medium thermal images to improve the accuracy of the TMTI method.

A. CO_2 Camera Data Extraction

Images from the CO_2 camera show a detailed view of breathing behavior, such as when a breath starts and stops, how the person is breathing, and how the exhaled air collides with and spreads across the medium. Information gathered from this camera informs our understanding of the circumstances occurring for each frame from the medium-view camera. Breathing mode is one metric of interest to pulmonologists that can be obtained from the CO_2 camera images. Healthy individuals tend to breathe through their nose unless the nasal passage is obstructed, at which point the individual breathes either completely through their mouth, or through their nose and mouth simultaneously. By extracting breathing mode from the CO_2 camera images, we can label each medium-view image and use this data to train a CNN to classify the breathing mode of medium-view images.

To extract information from the side-view CO_2 camera images, we use the OpenCV [22] library to find the outline of the person's face through a combination of thresholding and morphological transformations. We process this data with the NumPy [23] Python module to find facial landmarks. The tip of the nose is the left-most pixel coordinate of the face, and the chinrest can be identified by taking the difference of the x-values of the pixel locations and finding the greatest peak. The chin and mouth are located between the tip of the nose and the chinrest, and are identified in a similar manner to the chinrest. We use these landmarks to mask unnecessary information and to extract the person's breathing mode. Breathing mode is determined by processing the pixels along the outline of the face using the SciPy [24] Python module, and looking for peaks in the data near the nose and mouth. No prominent peaks in the data indicate that the person is inhaling. We use this information to label each medium-view thermal image as one of four breathing states: not exhaling, exhaling through the nose, exhaling through the mouth, or exhaling through the nose and mouth.

B. Convolutional Neural Network Design

The medium-view images and the labels extracted from the CO_2 camera images are used to train a CNN that predicts breathing mode from the medium-view images. As an image classification problem, a CNN is well-suited for this task, but would likely benefit from some temporal context, as it is difficult to determine if the thermal signature on the medium is increasing or decreasing in temperature by examining a single image. To preserve some temporal context, we feed both the original image and the previous image subtracted from the current image to the CNN, which indicates if the medium temperature is increasing (exhale) or decreasing (inhale).

The CNN model is built using the Keras Python module with a TensorFlow backend [25] [26]. The CNN consists of a 2D convolutional layer with a Tanh activation map, a 2D max pooling layer with a (2x2) pool size, a flattening layer, and then a dense layer. The dense layer uses a softmax activation map to return label probabilities.

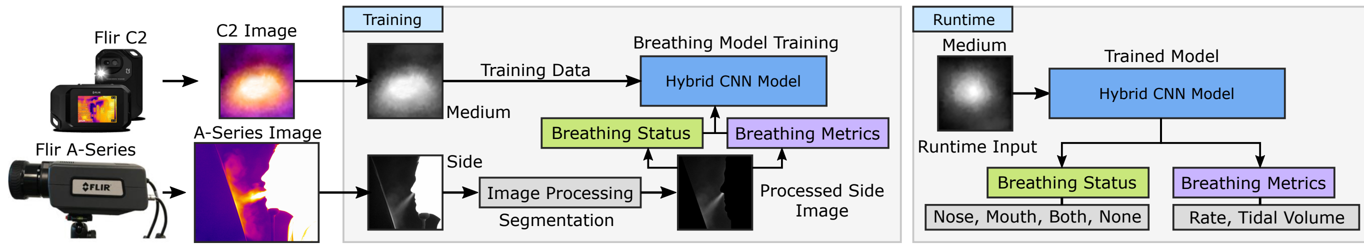

Fig. 3: Method overview: Medium and side images are used to build a reinforced exhale model for breathing analysis. This setup provides context to accurately monitor respiratory behaviors when the inexpensive medium monitoring method is used.

III. Experimental Design

During data collection, a test subject places their chin on the chin-rest and breathes onto the medium. Though this setup is admittedly not very comfortable, this experimental setup is designed to place constraints on the experimental parameters, and is not what we envision for clinical applications. Our aim through this experiment is to improve the accuracy of the original method so that in clinical applications, the patient can sit or recline in a comfortable position with the medium placed in line with the patient's exhaled airflow.

We've chosen paper as our medium material because it retains enough heat to be recorded by a thermal camera at a low framerate, but dissipates heat between breaths. Paper is also inexpensive, easy to find, and standardized. Figure 1 shows the experimental setup.

Test subjects that participated in this research were asked to provide six different samples of breathing data, approximately $60[s]$ each in length. They were asked to first provide the following four breathing samples while at a normal heart rate: (a) nose breathing, (b) normal mouth breathing, (c) breathing through a small mouth opening, and (d) breathing through a large mouth opening. Participants were then asked to provide nose and mouth breathing samples at a slightly elevated heartrate.

IV. Results

We collected approximately 4000 medium images from 4 individuals. All test subjects were healthy individuals with no congestion due to illness and no other breathing obstructions. Of the collected data, we excluded medium-view images that were matched with ambiguous side-view images, and abnormal images resulting from camera calibrations. This resulted in 2331 medium-view images and their associated labels and measurements.

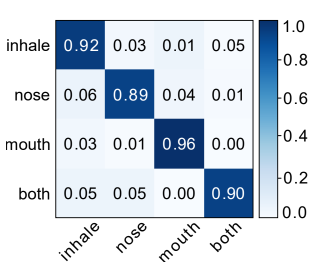

Fig. 4: Confusion Matrix

The collected medium-view images were composed of 1245 images where the individual is inhaling, 422 images of nose breathing, 587 images of mouth breathing, and 77 images where the subject is breathing through both their nose and mouth simultaneously. We iteratively separated the collected data into training data and test data, using a 75% to 25% split. We evaluated the performance of the CNN by running the evaluation 4 times with a different set of training and test data for each, and then calculating the accuracy of each prediction. Figure 4 shows a confusion matrix for one of the 4 evaluations of the CNN. The results show accuracies between 91.08% and 93.81% for the 4 training and testing splits.

V. Evaluation and Discussion

Breathing mode prediction performed with reasonable accuracy. Interestingly, the classification with the highest accuracy rate was the mouth, which is surprising due to the unique thermal signatures mouth breathing tends to produce compared with nose breathing. The CNN would likely be improved with additional training.

In the future, we plan to collect additional training data to continue to improve the accuracy of the system, and to also test the system with real-time data. We're also interested to see if we can apply machine learning techniques to other information extracted from the side-view images, such as determining the area of the medium that is directly heated by the initial contact with exhaled air instead of heated by the spread of the exhaled air after colliding with the medium.

VI. Conclusion

Respiratory monitoring is vital to the study of pulmonology, and standard contact methods value accuracy over patient comfort and alter natural breathing. The TMTI method of respiration monitoring strikes a balance between accuracy and patient comfort, while providing the ability to extract a variety of other respiratory metrics that are unattainable using other methods. We've shown that by augmenting the data collection procedure by using a reinforced hybrid model, we can examine exhale behaviors from a secondary view that further informs our understanding of the medium-view thermal images. We have also shown that a CNN trained with our current labeled medium images can be used to extract breathing characteristics with accuracies exceeding 91%. Through additional training and further feature extraction with more diversified conditions, we expect this method to achieve higher levels of accuracy and generality and be able to provide valuable respiratory information to medical professionals.

VII. Acknowledgements

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