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Covid-19, wearing N-95 masks in Clinical Environments: Thermographic Detection of Air Leaks

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Abstract

The presence of leaks in N95 masks represents a major issue and increases the risk of contamination. Usually, detecting these leaks is achieved manually and using expensive devices. The methods presented in this paper aim to automatically detect and locate leaks in N95 masks using recorded thermal image sequences. It is achieved by detecting the temperature variations on the skin around the N95 mask. These variations are closely related to leaks and are caused by the breathing. The first proposed approach consists in processing the infrared digital images where traditional methods such as the superposition and subtraction are employed. The second one employs a deep neural network architecture trained with labelled data before performing leak detection.

1. Introduction

During the CoVid-19 pandemic, a high number of cases have been observed in the health worker group. A study from the World Health Organization (WHO) [1] estimated the number of CoVid-19 death cases in this group, from January 2020 to May 2021, at 115 493. In October 2021 the WHO recommend the use of N95, FFP2 and FFP3 respirators or an equivalent for all the health worker group in contact with patients diagnosed with CoVid-19 disease [2] for a better protection against particles in the air and the reduction of contamination risks.

Nevertheless, many factors might affect the protection level of these masks, i.e., the adjustment between the respirator and the face of the worker. An adequate adjustment is supposed to limit the leaks around the respirator, also reduce the contamination risk from pathogenic particle presents in the work environment. Clayton et al. [3] have shown that the major factor in the loss of protection levels of the N95 mask remains the leaks through the facial joint. It implies the need of a good seal between the respirator and the face to ensure a high protection level.

Some conventional tests assess the adjustment factor, but they often require technical expertise that involve expensive devices. Moreover, they do not provide the leak region visualization which could help the evaluation and give the opportunity to improve techniques, positioning and education. This adds the need for research and development for alternative methods of face seal evaluation.

The use of infrared thermography is one of the effective methods to assess in a contactless manner the N95 masks protection level. The thermal camera for leaks detection focuses on the visualization of the temperature changes on the facial skin that happened near the facial seal of the respirator. These temperature changes are caused by the breather leaking out of hot air at the joint [4].

Many applications of the infrared imagery in the respirator domain exist, but concerning the evaluation of the facial leak region and the respirator performance, the method has still a limited application. Roberge et al. [5] have detected a breather out leaks on many subjects with the experimentation of the infrared imagery technique. Harber et al. [6] achieved to detect leaks with the help of the infrared imagery on a four-point scale and they established a general relation between the score they got and the protection factor measured by the quantitative PortaCount machine. The infrared imagery has also been used to validate the approach of fluid dynamic calculation to quantify the leak sealing [7]. However, no study has been done to automate the detection and the qualification of the leaks sealing with the infrared imagery.

The main objective of this study consists in developing a method that detect and quantify leakages on the respirators wearer through infrared thermography. Two approaches have been studied, the first by digital treatment of the infrared imagery and the second using a deep neuronal network architecture. Both approaches will then be compared to a classical method to perform fit test. The results presented in this paper are preliminary for leak detection at the mask/head interface.

2. Methodology

The participants of this study were six men and two women with minimal experience of using respirator. Each participant has been assigning randomly a model of N95 mask (model 1: 3M 8210, model 2: MOLDEX 2200, model 3: NORTH 7140V). The image acquisition uses three different protocols presented below.

2.1. Digital processing of the infrared images

In first approach the participants were recorded for a period five minutes where the participants breathed normally. The exercise includes five different angles of the face: (a) top view ,(b) left side view ,(c) bottom view (d) front face view and (e) right side view (see Fig. 1). The movements of the participants have been limited during the experiment.

The infrared images have been recorded with the FLIR X8500 high resolution (1280x1024 pixels) camera. An approximate distance of one meter was maintained between the camera and the participant. Each image sequence has been taken under the form of a video for a period of one minute at 25 frames per second while the person was breathing.

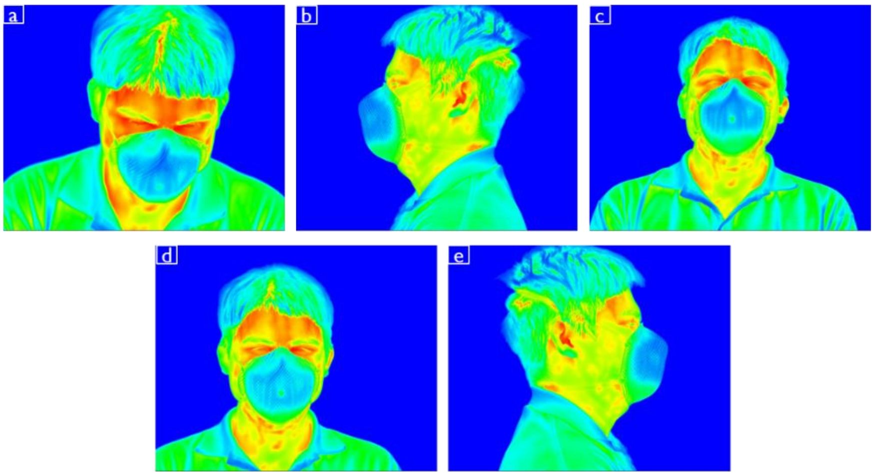

Fig. 1. *Example of infrared image from different point of view: (a) top, (b) left, (c) bottom, (d) front, (e) right.*

The first proposed approach for leak detection is based on infrared image processing from image sequences recorded using the protocol described in Fig. 1. Two distinct methods were employed: image superposition and image subtraction (see Fig. 2). The first is based on the superposition of two images, one from when the participant breathes in and the other from when he breathes out.

Due to head movement between the acquisition of the two consecutive images, a slight shift might be observed. Hence, before using such images, an alignment must be performed. In order to achieve that, the technique is the homographic matrix, which consist of finding similar points between the images. The points are compared, and it generates the homographic matrix. It is used to align all the corresponding points with a rotation, a shift, or a translation [8]. Once this step is completed, the only differences between the images are air leaks. For a better image selection for the breath in and breath out phases, an analysis of the red intensity mean (hot temperature) and the blue intensity mean (cold temperature) for each image of the sequence is performed and the images with the higher result (one for red and one for blue) are automatically extracted from the sequence. The second method is based on the segmentation of infrared images (background, face and mask) with the help of the application. After this step, the subtraction between the breath in and the breath out images can be made.

Once the subtraction is done, the leakage area can be extracted, as well as a measure of its importance is performed (i. e. surface area and intensity). To optimize the computation time in both methods, only the face area have been considered as a zone of interest (ROI) , the extraction of this zone was made with the originals images using the OTSU Thresholding approach [9].

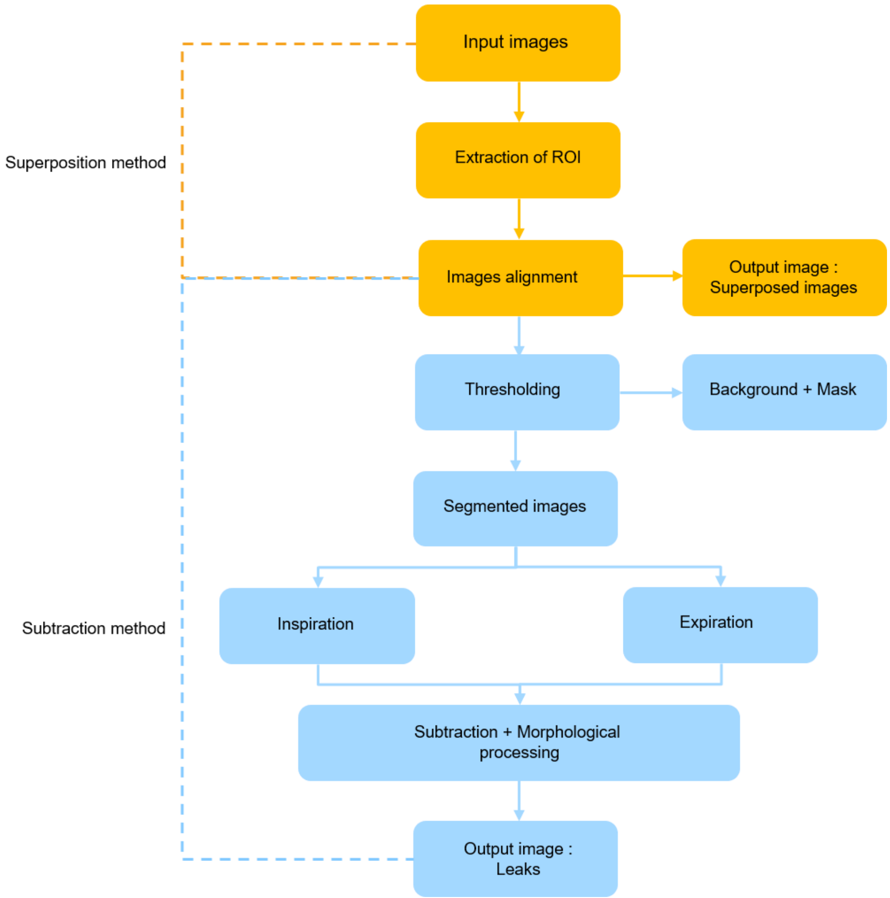

Fig. 2. *The techniques for images treatment with the superposition and subtraction method.*

2.2. Artificial intelligence

The second approach is based on using a deep neural network. The same protocol for image recording as the first approach has been used and the infrared images of the participants were recorded for a period of one minute. Normal breath and head movement were required during this protocol (see Fig. 4). The infrared images were acquired with the same high-resolution camera as in the previous protocol, and with the same parameters.

The deep neural network used in the present case is the Mask R-CNN, which made the implementation of a mask for the segmentation of the desired region based on the Fast R-CNN network [10]. The Mask R-CNN is based on the ResNet-101 architecture (see Fig. 3). Before labelling the image, a redefinition of the image size was done to reduce computation time for the network, the dimension selected is 512x512 pixels. Once this is in place, the labelling of the image that contain leaks was made manually for training. A json file is generated with all the information. With the *json* file, it is then possible to train the deep neuronal network model to detect leaks around the joint. To minimize the complexity of the training, we relied on the pretrained COCO model [11]. The training was able to generate the *h5* file which contains the weight of the different leaks of the model. The generated model was used to detect leaks.

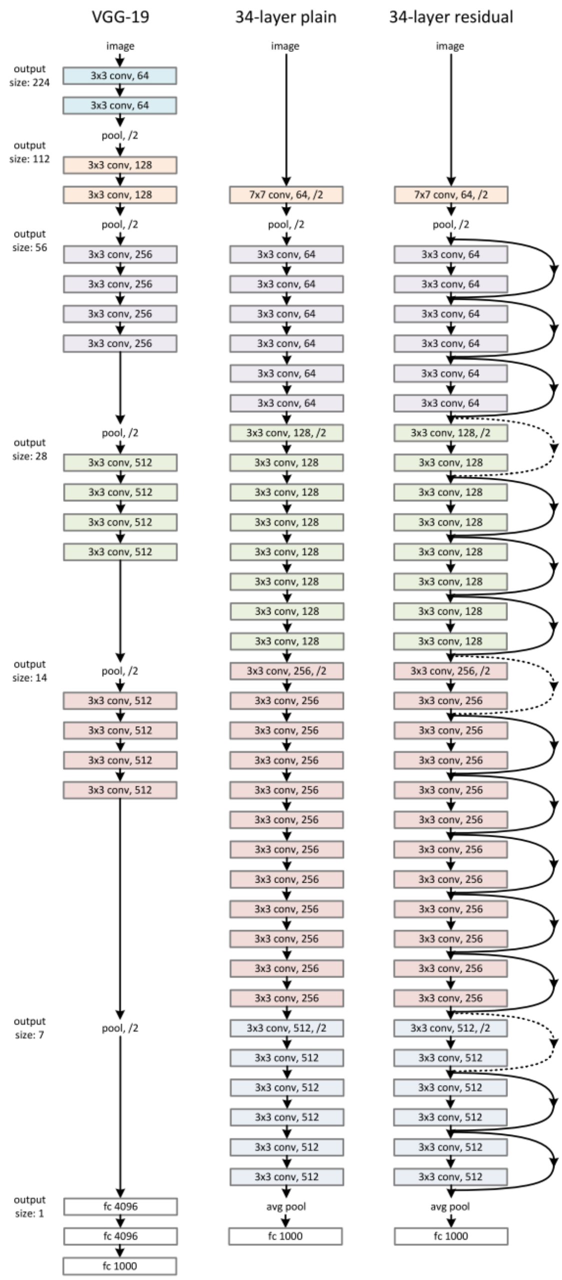

Fig. 3. *Architecture of the ResNet-101 used in Mask R-CNN [11].*

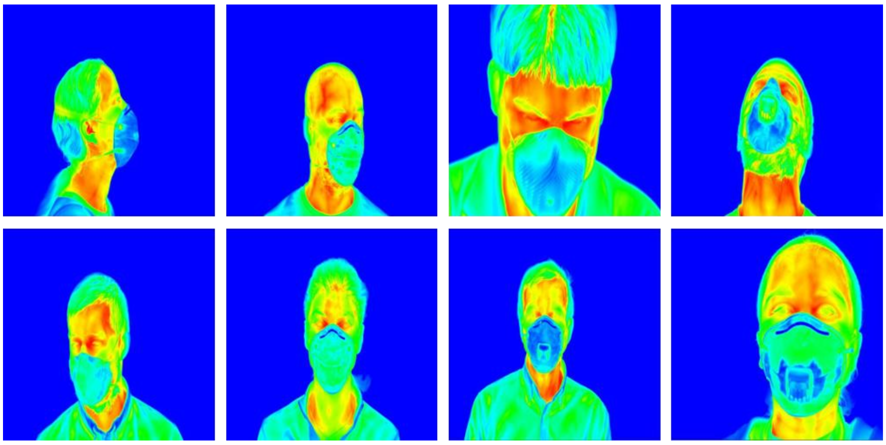

Fig. 4. *Illustration of some images from the dataset.*

2.3. Quantitative fit test

Four of the participants have been assigned to a quantitative fit testing (QNFT). The QNFT is a NIOSH approved method of testing the fit of N95 respirators and it is an objective and really accurate method for assessing fit. The QNFT was performed with a TSI PortaCount Pro+ model 8038 (see Fig 5). The device measures particles with a minimum size of 0.02 micrometers at a sampling flow rate of 350 cm^3/min. Fit tests were conducted using the OSHA protocol 29 CFR 1910.134 [12], which contains a series of eight exercises (see Box 1). To generate an overall fit factor score, the Fit Test Mode of the PortaCount Pro tests fit during the consecutive exercises. The overall fit factor is then calculated using the following formula:

$$Overall\ FF = \frac{n}{\frac{1}{FF_1}+\frac{1}{FF_2}+\cdots+\frac{1}{FF_n}}$$

where: FF_x = fit factor for test cycle (exercise)
n = number of test cycles (exercises).

FF ≥100 was classified as "pass" and FF <100 was classified as "fail." If FF was more than 200, the PortaCount assigned an FF of +200.

Box 1. *OSHA protocol 29 CFR 1910.134 [12]*

- Exercise 1 : normal breathing 60 seconds
- Exercise 2 : deep breathing 60 seconds
- Exercise 3 : turning head side to side 60 seconds
- Exercise 4 : moving head up and down 60 seconds
- Exercise 5 : talking 60 seconds
- Exercise 5 : grimace 15 seconds (this exercise is excluded in the calculation of FF)
- Exercise 7 : bending over 60 seconds
- Exercise 8 : normal breathing 60 seconds

Fig. 5. *PortaCount Respiratory Fit tester 8038.*

3. Results

3.1. Digital images treatment

The approach of digital infrared images processing, which is the superposition, or the subtraction provide slightly similar results. The Fig. 6 shows that the leak detection has been made at the level of the eyebrows, eyelashes and the hair, this can be explained by the presence of a leak in the nose area.

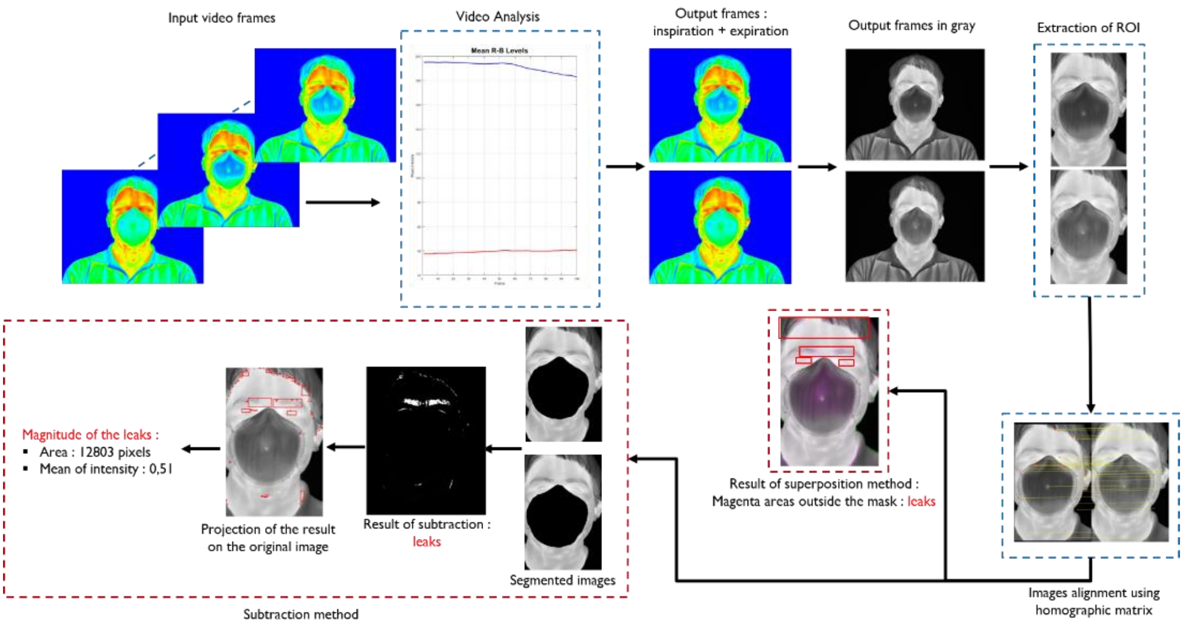

Fig. 6. Study case examples with digital images treatment approach.

The comparison between the magnitude of the leaks estimates with the subtraction method and the adjustment factor measure with the quantitative fit test gives the following results (see Table 1):

Table 1. *Comparison between subtraction method and fit factor.*

Participant	Mask type	Magnitude of the leaks		Fit Factor									
		Area (pixels)	Mean intensity	Ex.1	Ex.2	Ex.3	Ex.4	Ex.5	Ex.6	Ex.7	Ex.8	Total fit factor (FF)	Result
1	Moldex 2200	12803	0,51	11	8	6	6	10	Excl.	9	9	8	Fail
2	3M 8210	4627	0,25	34	44	37	31	30	Excl.	81	26	36	Fail
3	3M 8210	1161	0,22	200+	200+	200+	200+	200+	Excl.	200+	200+	200+	Pass
4	3M 8210	47321	1,16	7	4	3	3	7	Excl.	2	3	4	Fail

From these results, one can see that only the third participant had successfully passed the fit test made by the PortaCount device. A comparison with the results obtained with the thermal camera shows a small leak with a very small magnitude. For all the other participants, an augmentation of the leak magnitude (surface area and mean intensity) have been observed with a lost in protection (fit factor).

3.2. Artificial intelligence

The second approach using the deep neuronal network Mask R-CNN is promising. The results obtained, which are preliminary, can identify a leak (see Fig 7), but at this moment it only works well on the images we used to train the model. The results on the figure 5 were compared with a corresponding hand-labelled image where leaks were identified.

The training had only used 462 images from five different persons. One can suggest that the results can be improved with more images and also from different people who have different facial characteristics. To be able to achieve these results, the neural network was trained with the following configuration: 20 epochs, 100 steps and 70% of minimal detection.

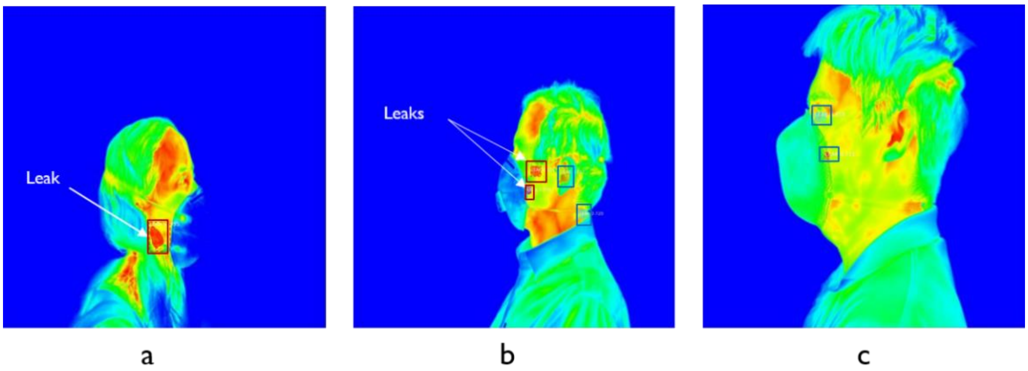

Fig. 7. *Illustration of some successful and failed case: (a) leak detection on cheek area, (b) two leaks detection on left cheek and two false detections (blue square), (c) two false detections (blue square).*

4. Conclusion

In this paper, two approaches have been discussed. These two approaches able to identify and locate leaks at the interface mask/head. The results can then be compared to a classical method to obtain a quantitative fit testing (QNFT). It is a NIOSH approved method, using a commercially available device with an OSHA protocol.

The first one consists in the direct image processing: it was the easiest and the fastest way to detect and quantify leaks. Also, the results show that it could be possible to establish a measurement scale with the PortaCount measuring device. We tested two digital image processing methods: superposition and subtraction. Both achieved similar results. Keeping the person not moving in front of the camera for this process is the biggest challenge.

A second approach, more accurate, based on the generalization capabilities of the deep neuronal network was tried. This approach is more complex and requires a large dataset of labelled images. An automatic labelling could be done first using the digital image processing approach and then the deep neural network can be trained with the images produced. Sometimes false positives appear far from the edge of the N95 mask. To prevent this, the idea is to first detect the contour of the N95 mask with the Mask-RCNN so all the false positives that are not close enough to the joint of the mask will be deleted to keep only the true positives. The results from deep neuronal network approach is very preliminary and should be taken as a first experimentation.

5. Acknowledgments

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