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Patient's Breath Detection and Monitoring System Using Webcams

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***Abstract*—This paper is based on embedded system and image processing using double Webcams to design a monitoring system for breath detection (EMSFBD) which monitors and records the patient's breath and sends the information to a specific server through the Internet. In this design image processing methods are used to monitor and record human breath fluctuation and to calculate the breath rate. If the breath rate is too low, too fast or if an individual's breathing stops for more than 10 seconds, our design sends out an alarm signal. Our EMSFBD consists of two parts. For the first part double Webcams are used to capture images and to transmit them to an embedded board. For the second part an image processing program using a temporal differencing algorithm to detect chest expansion and contraction to determine the breath rate is installed in the embedded board.**

***Index Terms*—Monitor System; Double Webcams; Temporal Differencing Algorithm**

I. Introduction

The traditional way of monitoring a patient's breath rate requires contact with the body by tying a device to it. For example, for Impedance Pneumography the electrode, which is placed on the skin of the chest, sends a high-frequency current and simultaneously uses the receiving electrode to receive any current changes during breathing. Respiratory inductive Plethysmography, which uses elastic bandages to tie wrapped wires on the human body, monitors breathing by checking the changing resistance. At the present time most methods require some sort of tying up or other contact with the body. Thus there is a need to design a method of breath detection that avoids this.

Our design detects chest expansion and contraction in a way that is similar to the detection of a moving object [1]-[3] by image processing. There are three major methods for detecting a moving object. First, "Temporal Differencing" [4] is used to find the difference between two continuous image data and to obtain any changes in the volume of a moving object [5]-[7]. If the background variation is not great, this method works well. Its disadvantage is that it is unable to discover the outline of the moving object completely. Second, "Background Subtraction" [8]-[9] is used to establish the background of the images and then input one image after another both to cancel the background and to obtain the moving object [10]-[12]. This method, which is able to detect a complete outline of moving objects, is very sensitive to changes in the environment because the background is established from the very beginning. Third, "Optical Flow" calculates the time for moving locations for each pixel in a specific image [13]-[15]. As this method requires a large amount of computer processing, its use in an embedded board seriously affects the computation efficiency. In our design, we use "Temporal Differencing", which has a higher image processing speed and whose use in the embedded board will not cause much of a burden [16]. In order to protect the patient's privacy, our EMSFBD records both the parameters and the process images instead of recording the original images.

II. Operation Environment of the System

The Fig. 1 shows the operation environment of the EMSFBD. The system sends images captured by the double Webcams to the embedded board where through digital image processing it determines the breath rate of the human body to detect whether the breath rate is normal. The LCD displays the real-time status of the breath rate on the embedded board. If no signs of life are detected, a warning message is sent to the hospital by means of the network interface board. We use an embedded board instead of a PC because of the low-power consumption and portability. In addition, the embedded board can reduce the cost.

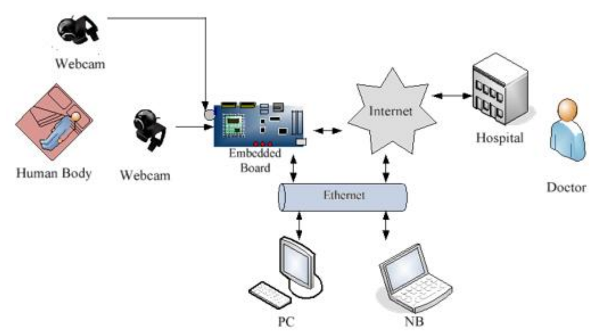

Fig. 1. The operation environment of the EMSFBD

III. Using Temporal Differencing Methods to Detect Micro-Vibration

The "Temporal Differencing" method uses two continuous images for subtraction to detect moving objects. It quickly adapts to changes in lighting or background. Although this method may detect the separate parts of moving objects, we can also detect a specific moving object. When the body is far away from the Webcam, we use the nearest neighboring interpolation method to enlarge the images. The enlarging method calculates the zoom ratio and then determines the new pixel of the new images.

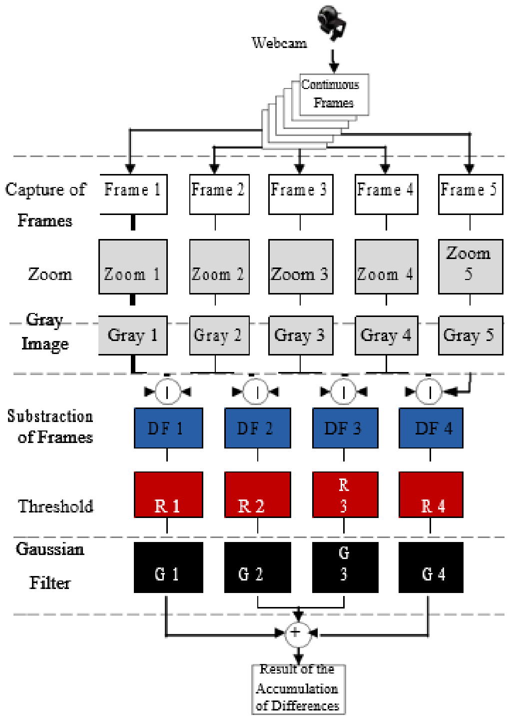

Fig. 2. Flowchart of the accumulation of the differences and the elimination of noise

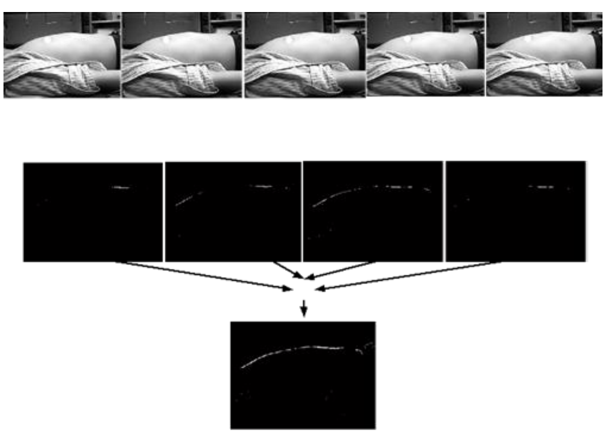

Fig. 3. Images after the subtraction of the cumulative chest displacement

The Fig. 2, shows the "Temporal Differencing" method which reads the continuous image from the Webcam, then fetches the separated images, processes them at the gray level and then enlarges the images of the particular object. This method finds the subtraction of the continuous images, chooses the threshold value for the decision, uses a Gaussian filter to remove any noise and then obtains the chest displacement in breathing as shown in Fig. 3.

The Fig. 4, shows the comparison of the chest displacement in breathing before and after the Gaussian filter. After the Gaussian filter processing, the previous noise in the picture has already been removed. The Gaussian filter is a smoothing filter where the degree of smoothing is controlled by the standard deviation σ; when the σ value is larger, the degree of smoothness is higher. Gaussian filtering can reduce misjudgment generated by the binarization noise or caused by moving dust particles, thus enabling us to more accurately detect the results of dynamic objects. The Gaussian distribution function is defined as

$$f(x,y) = \frac{1}{2\pi\sigma^2} e^{\frac{-x+y}{2\pi\sigma^2}} \tag{1}$$

x, *y* are the coordinates.

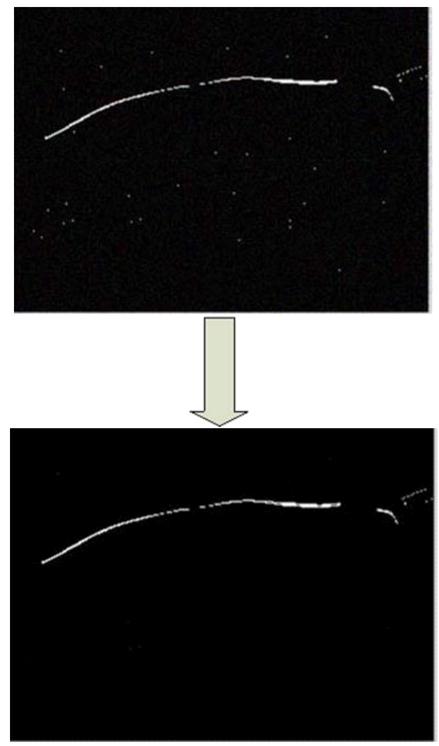

Fig. 4. Gaussian filter implementation diagram

IV. Breath Monitoring Algorithm

The Fig. 5 shows the flowchart of the detection of the breath rate. One path follows the normal order of subtracting the captured images, and the other path runs contrary to that order. This algorithm calculates the area of the two paths after displacement and obtains the direction of the chest movement. At the turning point the direction of the movement changes from that of the last record, and three accumulated turning points make a complete breath cycle.

The subtraction of two continuous images results in different values when read in a different order of images. It is stored in the matrix, and the elements are reset to zero if this subtraction is negative, because the size of the 8-bit grayscale element is 0-255. The human body's complete breath consists of the chest rising and falling, from maximum to minimum. If the chest rises to its maximum and then not only falls but also instantaneously changes direction, this development may cause a turning point. Three turning points make a complete breath cycle, and from that cycle we calculate the breath rate. In addition we use our digital method to enlarge the body movement to increase the detection distance.

The Fig. 6 shows the flowchart used to determine the physiological abnormalities. When the system detects no breath for more than 10 seconds, the EMSBD sends out a warning message. The judging method decides whether the patient's condition is normal or not by detecting the breath rate.

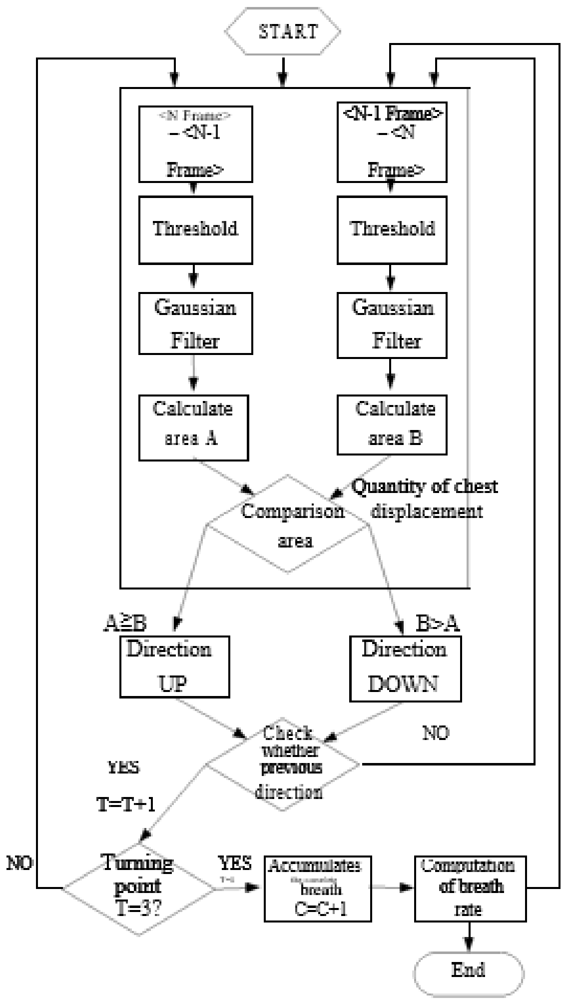

Fig. 5. Flowchart of breath rate detection

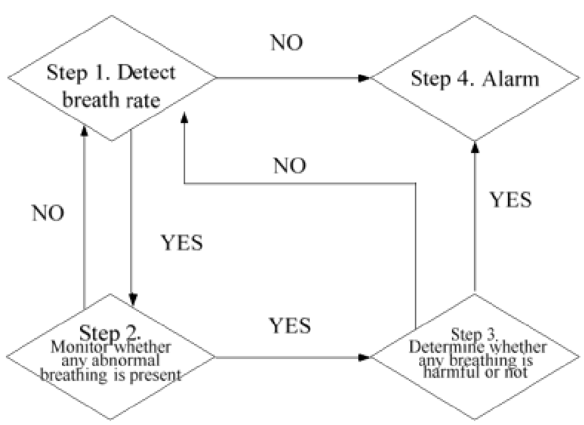

Fig. 6. Flowchart for determining physiological abnormalities

V. Implementation Results

The Fig. 7 shows the design with its integration of the embedded board with a Webcam. Our embedded board uses the kernel of ARM 11 whose maximum processing speed is about 667MHz. And it has the 3D Graphics Accelerator which can help the system process images easily. The sensor element of the Webcam is CMOS, which has 300,000 pixels and a focus from 20 mm to infinity. The core of the embedded system is the operating system, and our design uses both Linux and a C-code program to meet the efficiency requirements.

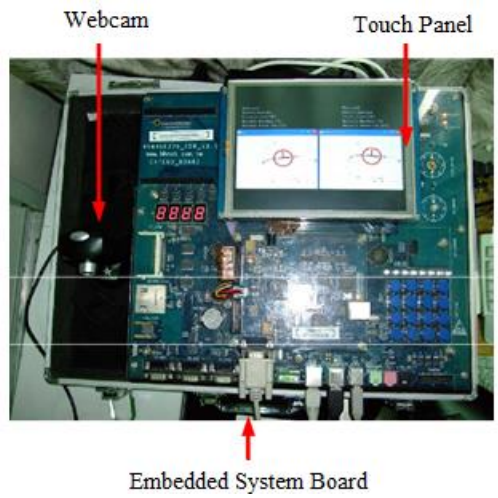

Fig. 7. Hardware of the EMSBD

Fig. 8 shows the software user interface of the EMSBD whose indicators show the direction of the movements of the ribcage when breathing as "up" or "down" on the LCD display.

We obtain one set of image data from the Webcams as shown in Fig. 8. Each group has four data which show "Direction", "Transition", "Number of Breaths", and "Breath Rate". "Direction" shows the direction of the thoracic movement which synchronizes with the chest moving targets in the area underneath the camera, "Transition" is the calculation of the cumulative transition, "Number of Breaths" calculates the total number of breaths, and "Breath Rate" shows the immediate breath rate. The relationship is shown in (1) and (2).

$$Breath\_Number = \left|\frac{Transitions}{3}\right| \tag{1}$$

$$Breath\_Rate = \left|\frac{Breath\ Number}{Time}\right| \tag{2}$$

The Fig. 9 shows the breath displacement diagram which demonstrates both chest expansion and contraction when the human body breathes. The horizontal axis of the diagram is the time in seconds, and the vertical axis is the distance in millimeters. We denote the transition when the directions of the two adjacent points in time are opposite each other. The accumulation of three transitions represents a full breath, as can be seen clearly from the chart in Fig. 9 which shows a recording time of 60 seconds with 19 full breaths. A normal man's respiratory rate is about 16 to 20 per minute, a woman's is about 18 to 22 and a newborn's is about 40 to 44. Thus a respiratory rate of 19 full breaths per minute is normal.

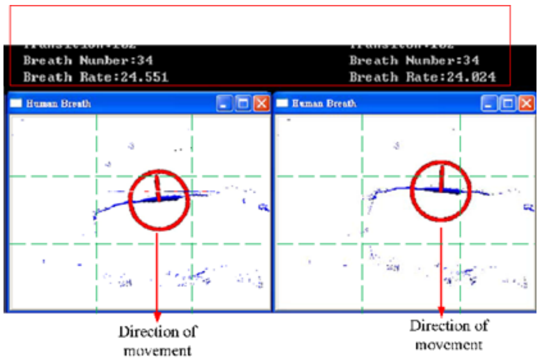

Fig. 8. Software interface of the EMSBD

The Fig. 10 shows the breath displacement diagram of Case 2, which has the same recording time of 60 seconds with 10 full breaths. Here the respiratory rate is 10 full breaths per minute. Obviously the respiratory rate is one full breath less than in Case 1. This result indicates that although the observed respiration is too slow, yet it still does not harm the body.

The Fig. 11 shows the breath displacement diagram of Case 3, which has the same recording time of 60 seconds with 8 full breaths. But as there are two breathing stops of 10 seconds, so the respiratory rate is 8 full breaths per minute. This result indicates not only slow breathing, but also that the amplitude of the chest movement is less than previously, and that there is a cessation of breathing for 10 seconds. The breathing of this individual, therefore, is already no longer normal.

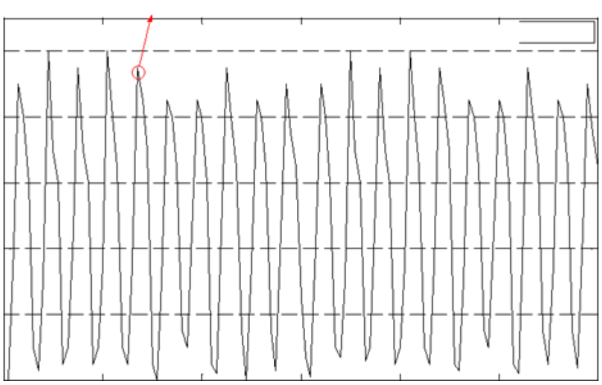

Fig. 9. Breath displacement diagram of Case 1

The Figs. 12 and 13 show the diagram of a long-time measurement of the sleeping breath rate, from 11:00 PM to 07:00 AM. The horizontal axis represents the time in units of a minute, and the vertical axis represents the breath rate. There are 480 pieces of information taken from each recording of the breaths of a minute. We see that the breath rate changes from 15 to 21.

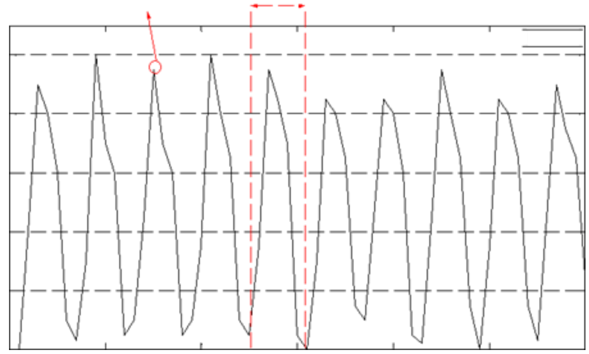

Fig. 10. Breath displacement diagram of Case 2

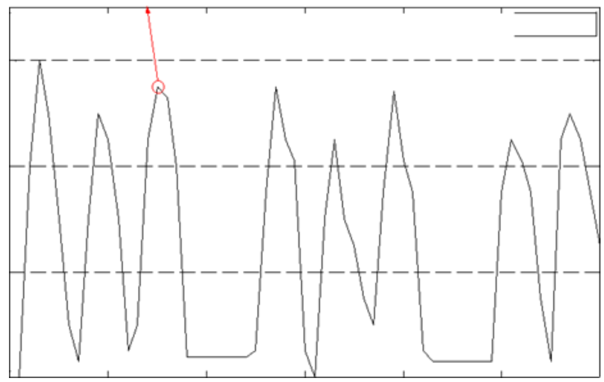

Fig. 11. Breath displacement diagram of Case 3

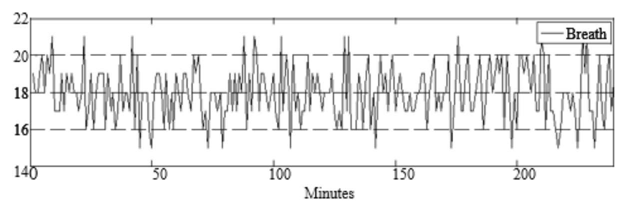

Fig. 12 (a). Breath rate diagram of part A

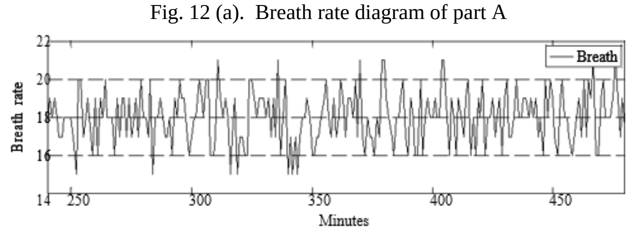

Fig. 12 (b). Breath rate diagram of part B

The Table I shows the Apnea record of an eight-hour measurement. We see continuous five-second and ten-second breathing stops. We focus on the intervals in 10 seconds, because if Apnea continues for more than 10 seconds this situation can be dangerous. We use the index to determine the sleep Apnea syndrome. Table II shows the Apnea syndrome divided into mild, moderate and heavy.

The Table III shows the comparison of our design and other design for breath detection. Our design, which not only is noninvasive and also provides remote breath monitoring without any body contact, can detect breathing for a long period of time without the patient feeling uncomfortable. In addition, it provides both alarm and recording functions.

TABLE I
APNEA RECORD

Duration Hour	**5 Seconds**	**10 Seconds**
1	1	0
2	2	0
3	0	0
4	0	0
5	0	0
6	2	1
7	0	0
8	0	0
Total	5	1

TABLE II
APNEA RECORD

Hour\Duration	Apnea Times
Mild	5-15
Moderate	15-30
Heavy	30 and Over

TABLE III
COMPARISON OF OUR DESIGN AND OTHER DESIGNS

	Our Design	Arterial Line	Respiratory Inductive Plethysmography
Platform	EMSBD	Bedside monitor	
Frames/Sec	25-30		
Resolution (cm/pixel)	Distance 0.8 cm 0.0056 60 cm 0.1666 4 m 0.2326 (Zoom 10 times)		
Invasive or not	noninvasive	invasive	invasive
Contact with human body	None	Yes	Yes
Detection distance	0.2m-8m		
Warning	Yes	Yes	Yes
Recording	Yes	Yes	Yes
Detection method	Image processing	Measurement of the concentration of O_2 and CO_2 in the blood	Measurement of the resistance change of the chest belt
Power Consumption	4.25 W	None	Unknown

The Table IV shows our comparison between a single Webcam and double Webcams. Using double Webcams, our design detects the breath of the human body allowing the body to flip. In addition to providing a wider detecting range, the double webcams also form an intersection region from which the Webcams can obtain two different sets of image data. Processing these two sets of image data results in informing the user of any necessary and reduces the possibility of any misjudgment.

TABLE IV
COMPARISON BETWEEN SINGLE WEBCAM AND DOUBLE WEBCAMS

No. of Webcams	May the body flip?	Calibration data	Detection range
Single webcam	No	No	Medium
Double webcams	Yes	Yes	Large

VI. CONCLUSION

Our design, the EMSFBD, uses double Webcams, the temporal differencing method and an embedded board to monitor the breath of the human body without the inconvenience of any contact with the body. In addition, our design can also monitor micro-vibration. For example, during an earthquake our design, which can detect the swing amplitude and the frequency of objects, can therefore, estimate the intensity of an earthquake.

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