Real-Time Non-contact Breath Detection from Video using Adaboost and Lucas-Kanade algorithm

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***Abstract*—A simple and economical system is developed to detect human breath in a real time fashion with a normal webcam. By using the optical flow method, a novel approach is proposed to detect the peak of inspiratory phase from a series of frames that are captured from a camera to define the time for trigging X-ray shooting. The issue of using images to detect breath is that the motions of respiratory features on chest are very small, since the camera is attached on the X-ray machine with a significant distance. Therefore, the Lucas-Kanade algorithm is considered to track small motions on chest. Adaboost and corner detection are developed to identify region of chest and to obtain useful feature points for the Lucas-Kanade algorithm. From the experimental conducted, by using the proposed approach, the motion of respiratory phase is easily observed and the predictive error of the peak time is about 0.488 second, approximately 9.75% of the averaging breath cycle. It is acceptable for the X-ray shooting purpose.**

Keywords*— *Breath detection, inspiratory phase, respiratory phase, detect respiration, Lucas-Kanade Algorithm, deepest inspiration.

I. INTRODUCTION

It is well-known that the quality of X-ray image for chest is the best obtained when the patient's ribcage is full of air, corresponding to the peak time of inspiratory phase. Therefore, the peak time of inspiratory phase plays an important role in enhancing quality of X-ray image. Various methods have been proposed to detect breath. Basically, there are two kinds of approaches: contact and non-contact. The contact approaches use wearable sensors such as thermistors, ribcage inductive belt [1, 2] to directly detect breath.

Non-contact approaches use infrared camera to capture the temperature of nasal region [3, 4], use microphones [5] to gather sound signal near the nose, or use normal webcams to apply the temporal differencing technique to find vertical motion of chest [6, 7]. Another method uses a smooth reflex surface to reflect low-power laser beam onto the wall. Then a webcam is used to monitor the laser projection on the wall [8]. A novel approach gets features on face to visualize the blood flow and reveal small motion [10]. G. Balakrishnan, F. Durand, and J. Guttag introduced a new method to reveal heart rate and beat lengths [11] by measuring subtle head motion caused by blood circulation.

In this paper, after this introduction, the whole system is introduced in section II. The extracted features inside the chest region are discussed in section III. In section IV, the novel approach that uses the Lucas-Kanade algorithm to get the breath motions from the features is presented. In section V, the peak detection of inspiration phases is discussed. The experimental results are presented and discussed in section VI. Finally, conclusions are given.

II. SYSTEM DESCRIPTION

A. System Overview

The system of breath detection is very simple, since it only requires a standard computer to connect with a normal webcam (Fig. 1). When the peak time of inspiratory phase is detected, the ddRElement™ X-ray machine will be triggered to capture X-ray image automatically.

Fig. 1. Logitech webcam C920

B. The Algorithm of Breath Detection

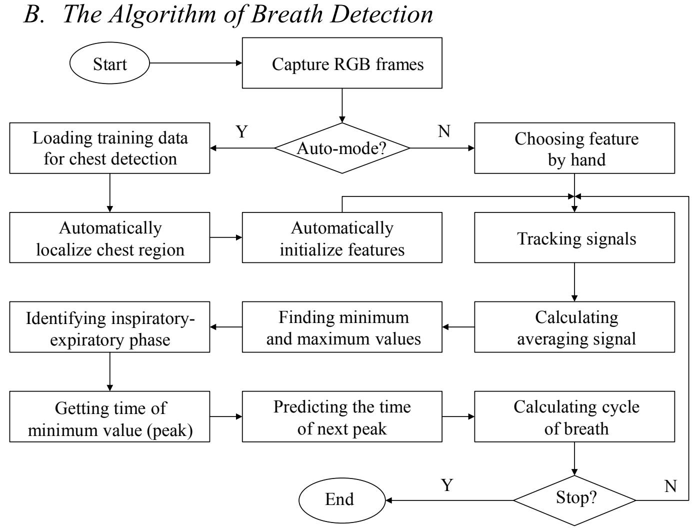

Fig. 2. Algorithm for breath detection

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Basically, the proposed algorithm has two modes: automatic mode and manual mode. The automatic mode is to use the training data based on the algorithm of Viola-Jones [17] to detect the region of chest. The features on chest region are then automatically initialized for tracking positions. The manual mode creates features by choosing the designated points on chest region. All feature points are then tracked between two continuous frames to get signals of positions $\{x_n(t), y_n(t)\}$ by applied the Lucas- Kanade algorithm. Only the vertical points $y_n(t)$ is used in our analysis. Averaging signal is calculated to analysis breath signal for identifying respiratory phases, cycle of breath, and the peak time of the deepest inspiration.

III. FEATURE EXTRACTION

A. *Training data to recognize chest region*

To detect the chest region, 1000 positive images and 2000 negative images are prepared for training images based on the Viola and Jones algorithm [17]. Firstly, features are extracted by applied a set of Haar features. Basically, the set of Haar consists of three kinds of features (two-rectangle, three-rectangle and four-rectangle feature) as shown in Fig. 3. The value of a rectangle feature is defined by the sum of the pixels which lie within the black rectangle subtracts the sum of pixels in the white rectangle.

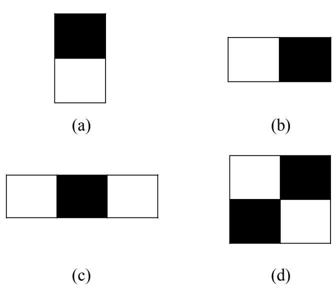

Fig. 3. Two-rectangle features are shown in figure (a) and (b). Figure (c) shows a three-rectangle feature, and (d) a four-rectangle feature

Rectangle features of positive and negative images are computed very rapidly using integral image. The Adaboost is then used both to collect the important features and train the classifier. Finally, the strong classifiers are constructed into a cascade of classifiers which helps to increase detection performance and to reduce computation time.

B. *Corner detection*

To apply the optical flow method, the corners must be defined to locate the position of good features. Calculating gradients for matrix M is performed as equation (1):

$$M = \begin{pmatrix} \sum I_x^2 & \sum I_x I_y \\ \sum I_x I_y & \sum I_y^2 \end{pmatrix} \tag{1}$$

The eigenvectors and eigenvalues (λ_1, λ_2) of matrix M are calculated to find out the predominant directions and magnitudes of gradients. The corners are spots that get the minimum value of R= min($|\lambda_1|$, $|\lambda_2|$), and R must be over a threshold.

IV. MOTION DETECTION

The trajectories of good features on chest are tracked over the time to get the averaging signal. Supposed that the brightness is constant, the two continuous frames must be satisfied the following equation:

$$I(x,y,t) = I(x+dx, y+dy, t+dt) \tag{2}$$

$$\Leftrightarrow I(x,y,t) = I(x,y,t) + \frac{\partial I}{\partial x}dx + \frac{\partial I}{\partial y}dy + \frac{\partial I}{\partial t}dt \tag{3}$$

$$\Rightarrow \frac{\partial I}{\partial x}dx + \frac{\partial I}{\partial y}dy + \frac{\partial I}{\partial t}dt = 0 \tag{4}$$

$$\Rightarrow I_x dx + I_y dy + I_t dt = 0 \tag{5}$$

$$\Rightarrow I_x u + I_y v = -I_t \tag{6}$$

To apply the Lucas-Kanade algorithm, the motion of features between two continuous frames must be small and approximately constant within neighborhood of the point p. Therefore, to solve the optical flow equation (6), a window centered at p is used to determine the local flow vector (u, v) as shown in equation (7).

$$\begin{matrix} I_x(\mathrm{q}_1)\,\mathrm{u} + I_y(\mathrm{q}_1)\,\mathrm{v} = -I_t(\mathrm{q}_1) \\ I_x(\mathrm{q}_2)\,\mathrm{u} + I_y(\mathrm{q}_2)\,\mathrm{v} = -I_t(\mathrm{q}_2) \\ \vdots \\ I_x(\mathrm{q}_n)\,\mathrm{u} + I_y(\mathrm{q}_n)\,\mathrm{v} = -I_t(\mathrm{q}_n) \end{matrix} \tag{7}$$

Where $I_x(q_i)$, $I_y(q_i)$ and $I_t(q_i)$ are derivatives of the image I following x-direction, y-direction of the image, and the time t respectively; q_1, q_2, …, q_n are the pixels inside the window. The equation (7) can be written as matrix form $AX = b$, where

$$A = \begin{bmatrix} I_x(\mathrm{q}_1) & I_y(\mathrm{q}_1) \\ I_x(\mathrm{q}_2) & I_y(\mathrm{q}_2) \\ \vdots & \vdots \\ I_x(\mathrm{q}_n) & I_y(\mathrm{q}_n) \end{bmatrix}, \quad \mathrm{X} = \begin{bmatrix} u \\ v \end{bmatrix}, \quad and \quad b = \begin{bmatrix} -I_t(\mathrm{q}_1) \\ -I_t(\mathrm{q}_2) \\ \vdots \\ -I_t(\mathrm{q}_n) \end{bmatrix} \tag{8}$$

There are two unknown variables (u, v) while more than two equations. Therefore, it is solvable by using the least squares principle.

$$A^T A X = A^T b \qquad \text{or} \qquad X = \left(A^T A\right)^{-1} A^T b \tag{9}$$

$$\begin{bmatrix} u \\ v \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{n} I_x(\mathrm{q}_i)^2 & \sum_{i=1}^{n} I_x(\mathrm{q}_i) I_y(\mathrm{q}_i) \\ \sum_{i=1}^{n} I_y(\mathrm{q}_i) I_x(\mathrm{q}_i) & \sum_{i=1}^{n} I_y(\mathrm{q}_i)^2 \end{bmatrix}^{-1} \begin{bmatrix} -\sum_{i=1}^{n} I_x(\mathrm{q}_i) I_t(\mathrm{q}_i) \\ -\sum_{i=1}^{n} I_y(\mathrm{q}_i) I_t(\mathrm{q}_i) \end{bmatrix} \tag{10}$$

To detect breath, the good features are tracked by the Lucas-Kanade algorithm to get the averaging signal. The position of averaging signal following x-direction and y-direction are shown in Fig. 4 and Fig. 5, respectively.

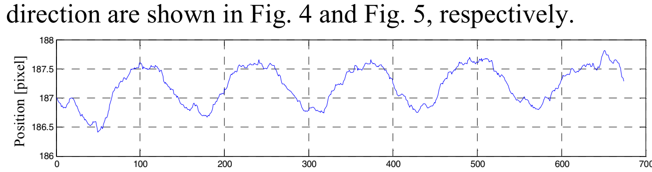

Fig. 4. X-direction (horizontal) signal on chest

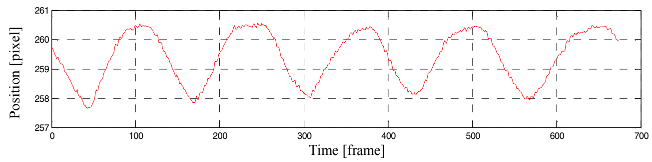

Fig. 5. Y-direction (vertical) signal on chest

Since the vertical (y-direction) signal is better than the horizontal (x-direction) signal. Therefore, the vertical signal is chosen for further process.

V. PEAK IDENTIFICATION

Minimum and maximum values are determined from the averaging signal to identify the phase of respiration. From Fig. 6, the minimum values and maximum values represent for the time of deepest inspiration and expiration, respectively.

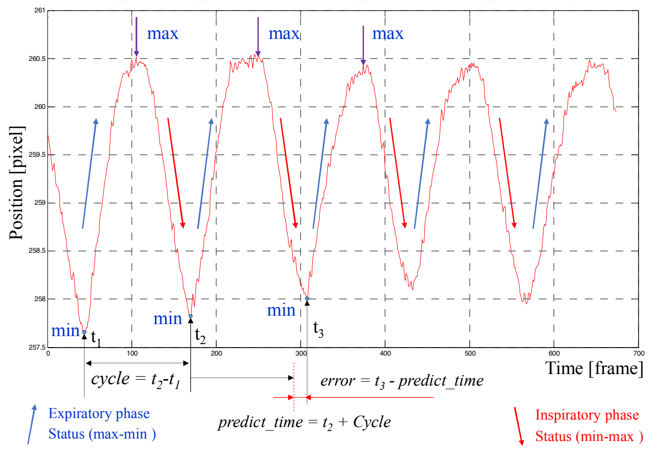

Fig. 6. Identify inspiratory-expiratory phase

Phases of respiration are identified by a Boolean variable ("Status"). True or False value is set for "Status" if the signal gets the minimum or maximum value, respectively. False value represents for inspiratory phase and True value represents for expiratory phase.

Supposed that t_2 is the current peak time of inspiratory phase as shown in Fig. 6. The cycle of breath is calculated by subtracting the previous peak time (t_1) from the current peak time.

$$cycle = t_2 - t_1 \tag{11}$$

The next peak time is predicted as

$$predict\_time = t_2 + cycle \tag{12}$$

The error between the actual peak time (t_3) and the predicted peak time is calculated as

$$error = t_3 - predict\_time \tag{13}$$

VI. EXPERIMENTAL RESULTS

A. Analysis the fluctuated time between the actual and predicted peak of inspiration

In this section, data of five people with the age from 25 to 30 are collected in one minute to analysis the fluctuated error between the predicted and actual peak time of inspiration. Five features are chosen on chest to get the averaging signal and then analysis this signal to find out the errors following the equation (13).

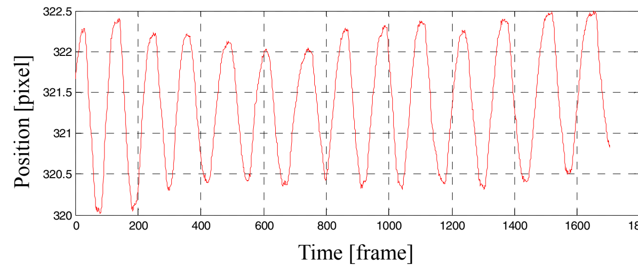

Fig. 7. Averaging signal in one minute

The averaging signal in one minute is recorded as shown in Fig. 7. The processing time for the camera that has 30fps is 33.33 ms. In fact, the processing time of Swissray system is 34.277 ms (approximate 29 fps). From Fig. 8, almost errors fluctuate around 15 frames, that corresponding to 15*34.277 = 514.155 [ms].

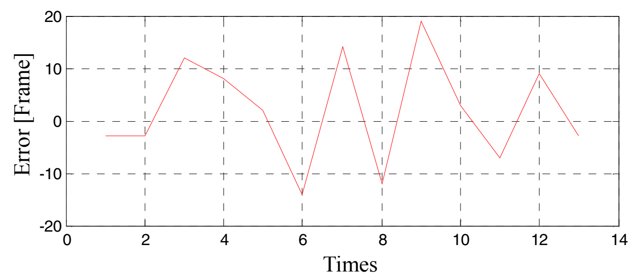

Fig. 8. Fluctuation between predicted and actual peak time

TABLE I
STATISTIC OF FLUCTUATED TIME IN ONE MINUTE

	0-4 [frame]	5-9 [frame]	10-14 [frame]	15-30 [frame]	Processing time [ms]
Viet	5	3	4	1	34.277
Quan	2	5	6	0	34.665
Truong	5	3	3	1	34.860
Julie	3	2	3	4	34.932
Yizhong	0	3	7	2	35.432
Sum	15	16	23	8	34.833

The averaging breath cycle of five people is around 5 seconds. From Table I, the averaging processing time is 34.833 ms (approximate 29 fps). 24.19%, 25.81%, and 37.1% errors distribute in 0-4, 5-9, and 10-14 frames, respectively. Therefore, nearly 90% of errors distributes in 0-14 frames, corresponding to fluctuated processing time from 0 to 487.662 ms. It accounts for 9.75% of averaging breath cycle. It is acceptable for real time application.

B. Analysis the impact of number of feature points to processing time

This part tests the relationship between the number of feature points and processing time. Manual mode is chosen to test different number of feature points (1, 20, 40, 60, 80, 100) on chest in one minute. Table II indicates that the number of feature points is directly proportional to the processing time while inversely proportional to the frame rate. Therefore, to enhance performance, the number of feature points should be chosen as low as possible.

TABLE II
DATA OF PROCESSING TIMES AND NUMBER OF FEATURE POINTS

Number of feature points	Processing time [ms]		Averaging frame rate	
	Core i5	Core i7	Core i5	Core i7
1	37.5	33.878	26.667	29.512
20	40.5	33.921	24.691	29.480
40	40.6	34.052	24.631	29.367
60	40.7	34.181	24.570	29.256
80	42.3	34.247	23.641	29.200
100	42.7	34.300	23.419	29.155

In our experiments, the number of features from 1 to 60 is recommended for weak configuration computer to obtain a good processing time as shown in Table II. However, some applications need to measure breath signal during a long time. The week features may be lost as shown in Fig. 9. Therefore, choosing features from 20 to 60 is recommended to guarantee the speed of frame rate and to avoid losing weak features.

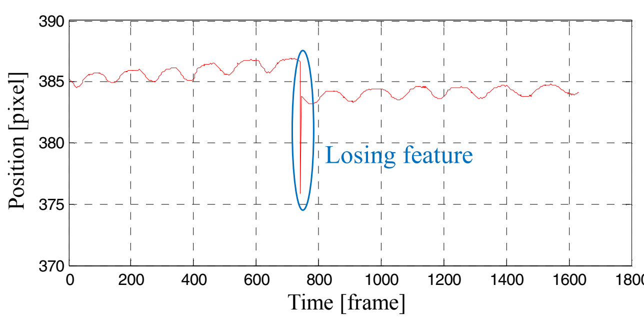

Fig. 9. Losing weak features over the time

VII. CONCLUSION

In this research, a novel non-contact approach is proposed to detect breath motions in real time. The proposed approach only use a normal webcam that connects to laptop without any other devices. Therefore, it has a low installation and maintenance cost. The Lucas-Kanade algorithm is very efficient to track trajectories of good features on chest. This approach can classify inspiratory and expiratory phase, calculate breath rate, and predict the peak time of inspiration. The time of deepest inspiratory phase is predicted with a high accuracy in a real time fashion. In our experiments, the predicted error of the peak time is 487.662 ms, which roughly accounts for 9.75% of the averaging breath cycle. In the future, this approach is developed to detect the breath of babies who are not able to lie statically on the x-ray table.

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