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Improvement in Accuracy of Respiration Pattern Detection on Visual Sensing System

Yoshio Miyake[a,c,d], Ken Ishihara[a], Hideyo Shinmori[a], Hiroki Otsuka[a], Hiroaki Nakai[b], Mutsumi Watanabe[b], Keisuke Takada[c], Kaoru Yamashita[d], Tsutomu Araki[d]

[a]Medical Informatics, School of Medicine, Ehime University, Ehime, 791-0295, Japan
[b]Kansai Research Laboratories, Toshiba Corporation, Kobe-shi, Hyougo, 658-0015, Japan
[c]Toshiba Engineering, 66-2, Horikawa-cho, Saiwai-ku, Kawasaki-shi, Kanagawa, 210-0913, Japan
[d]Graduate School of Engineering Science, Machikaneyama-cho, Toyonaka-shi, Osaka, 560-0043, Japan

Abstract

Non-restrictive monitoring of respiration of a patient is one of the most important tasks in the field of clinical care. We have already extracted frequency characteristics by inter-image subtraction from motion pictures that show motion of respiration (Visual Sensing System). However, there is a limit to elucidating physiological changes using motion pictures, due to S/N ratio, frame rate of video camera, and drift caused by salt and pepper noises. Our new work contains three algorithms to extract frequency characteristics optimally despite these limitations. The first is *adaptive interval setting*, in which we most adaptively set the interval for inter-image subtraction to optimally detect respiration patterns. The second is *adaptive threshold setting*, in which a threshold is most adaptively set for counting cross points so that respiration patterns on the curves, large or small, are not ignored. The last is *time averaging of image data*, which reduces the effects of salt and pepper noises. As a result, frequency characteristics in the darkness are recognized despite salt and pepper noises. This study improves the quality of respiration monitoring system that is an indispensable apparatus to keep patients' life.

1 Introduction

Non-restrictive monitoring of respiration of a patient is important in the field of clinical care. To extract frequency characteristics of motion at moving parts of motion pictures such as video images of human chest, inter-image subtraction is one of the efficient methods. We have already extracted frequency characteristics by inter-image subtraction from motion pictures that contain motion of respiration, as shown in Fig. 1 (Visual Sensing System)[1]. In this paper, we present the algorithms for enhancements in detection of respiration patterns.

In Section 2, the general view of the respiration monitoring system is explained, followed by Section 3 where the needs for enhancements of the system are explained. In Section 4, the algorithm for *adaptive interval setting* is presented. The algorithm for *adaptive threshold setting* is presented in Section 5, and the algorithm for *time averaging of image data* is presented in Section 6. The last section presents concluding remarks.

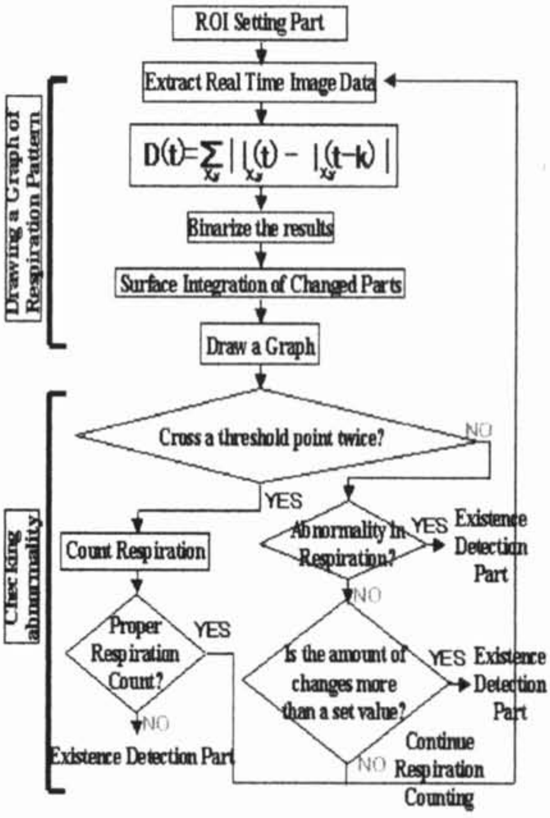

Fig 1 : Flow of respiration monitoring by inter-image subtraction on Visual Sensing System (respiration counting part)

2 Respiration Monitoring System

The respiration monitoring system consists of three major parts, 1) Existence detection part[2], 2) ROI setting part[3], and 3) Respiration counting part, as shown in Fig. 2. Existence detection part checks if there's somebody on a bed. If somebody is found on a bed, the system moves to ROI setting part. ROI setting part finds the best ROI for respiration counting. In case a proper ROI is found, the system moves to respiration counting part. Respiration counting part counts respiration using inter-image subtraction.

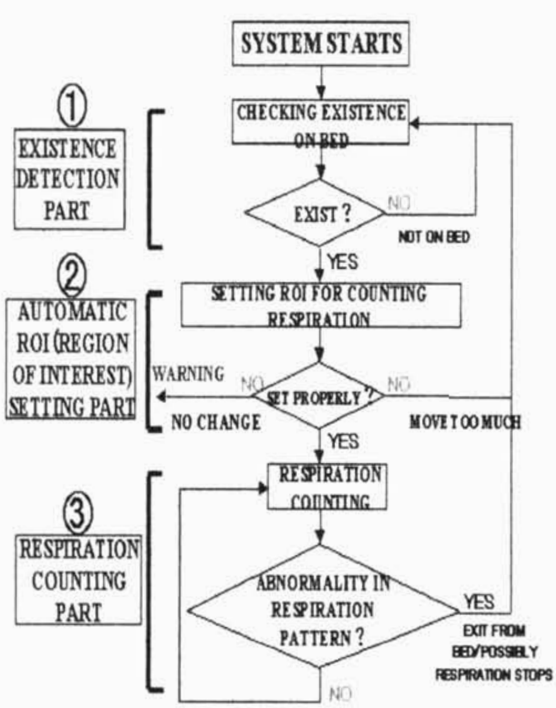

Fig 2 : Flow of Respiration Monitoring System

3 Needs for Enhancements

In inter-image subtraction at respiration counting part of the system, gray levels of each corresponding pixel at a region of interest (ROI) of two images are subtracted and the sum of their absolute values yields one scalar representing differences between the images. The amount of differences correlates to the changes in original motions that cause surface differences. Using results of inter-image subtraction, we can estimate physiological changes that cause differences between the images. However, there is a limit to elucidating physiological changes using motion pictures, due to S/N ratio, frame rate of video camera, and drift caused by salt and pepper noises. We have developed three algorithms to extract frequency characteristics optimally despite these limitations. All of them improve the accuracy of respiration pattern detection. The first is *adaptive interval setting* between two images taken for subtraction according to the frequency of respiration. The second is *adaptive threshold setting*. The third is *time averaging of image data* of video images.

3 Adaptive Interval Setting

Adaptive interval setting improves the accuracy of detection of respiration patterns by most adaptively setting the interval to take two images for subtraction, as shown in Fig. 3. Curves on the graph that represent changes in periodic motions on video images do not always match exact sine curves. For example, on the graph that shows the flow of respiration, amplitudes of curves that represent exhalation are smaller than the ones that represent inhalation. Even with the same physiological changes, amplitudes of curves on the graph sometimes become smaller, dependent on the way of distribution of gray level histogram at the ROI. Therefore, to extract frequency characteristics without ignoring smaller changes of respiration, respiration patterns on curves may better be emphasized. One of the methods for this emphasis is to set the interval for taking two images for subtraction to half the respiration period, which leads to subtraction between maximum and minimum points of curves. However, the respiration period changes dynamically and results of subtraction become the values taken for dynamically changing period of time, not the same duration of time. To attain the correct values for the flow of respiration at the same interval, we must divide each absolute value of subtraction by the number of images taken for the interval and multiply the result by a constant value.

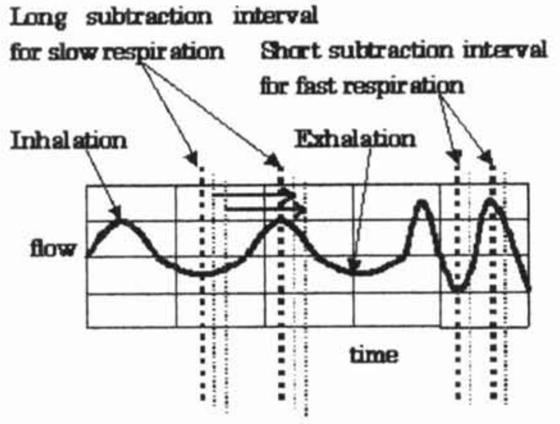

Fig 3 : Adaptive interval setting of inter-image subtraction. Subtraction between maximum and minimum points yields the largest difference.

4 Adaptive threshold setting

Adaptive threshold setting **improves the accuracy of respiration pattern detection by setting a threshold most adaptively, as shown in Fig. 4. In inter-image subtraction, where absolute values of subtraction results are used to yield changes in motion, salt and pepper noises at the ROI are added as positive values. As a result, curves on the graph drift in the positive y direction. Since such increments for each value on curves are approximately equal because of spatiotemporal randomness of salt and pepper noises, periodic nature of curves on the graph still remain on top of a constant upward drift. But, if the threshold to detect respiration patterns is fixed smaller for counting cross points, some maxima of curves are not detected as changes caused by respiration because minima between maxima of curves drift due to salt and pepper noises and curves do not cross the threshold. On the other hand, to avoid above problem, if the threshold is fixed larger to place minima under the threshold, some small maxima are not counted as changes due to respiration. To satisfy both needs, we most adaptively changed the way to set the threshold. If curves are coming up from minima, the threshold is set for counting cross points upward from the minima. If curves are coming down from maxima, the threshold is set for counting downward from the maxima. By this method even if minima between maxima of curves are not small enough, all the maxima of curves, large or small, are counted as changes due to respiration.**

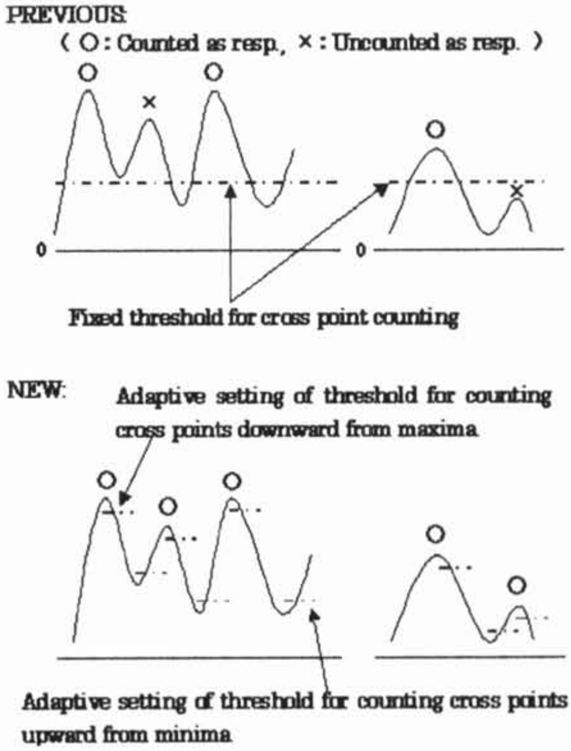

Fig 4 : Adaptive setting of threshold for counting cross points. Curves drift due to pepper noises. Previously, threshold was fixed for counting and some maxima were not counted as changes due to respiration. But, in the new version, by most adaptively setting a threshold for counting cross points, downward from maxima for downward curves and upward from minima for upward curves, all the maxima, large or small, are counted as changes due to respiration.

5 Time averaging of image data

Time averaging of image data **of video images reduces the effects of salt and pepper noises. In the darkness of gray levels smaller than around 10, the influences from salt and pepper noises increase because the changes in gray levels of each pixel due to respiratory movements as a result of inter-image subtraction are also very subtle. In order to extract frequency characteristics, we need to reduce the effects of salt and pepper noises. Also when a patient turns on a bed and an area of a ROI on a body that has been showing respiratory movements shifts, the respiration monitoring system searches for a new ROI that shows the largest changes in gray level as a result of inter-image subtraction. If salt and pepper noises exist on images, chances are that the system locates a**

new ROI at noisy parts on images. To solve the above problems, by using spatiotemporal random characteristics of salt and pepper noises, gray levels of each pixel of several sequential images are added and averaged, and as a result, gray levels increased by salt and pepper noises are flattened and ignored when the results of inter-image subtraction are binarized. In this way, the system can extract frequency characteristics of respiration in counting respiration, and can also find the best ROI that shows the largest changes in gray levels caused not by salt and pepper noises, but by respiratory movements in ROI setting.

6 Experiment and Results

We used the above system to monitor respiration of patients in bed. The patients' respiration was monitored for eight hours from 9 p.m. to 5 a.m.. The accuracy of counting respiration was 95%[4]. Figure 5 shows the curves obtained by plotting the results of inter-image subtraction. A rectangle indicates the time duration for ROI setting due to too fast respiration, where respiration was not counted. Figure 6 shows the same result taken for about two hours.

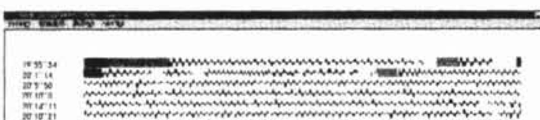

Fig 5 : Result of respiration monitoring. A rectangle indicates the time duration for ROI setting.

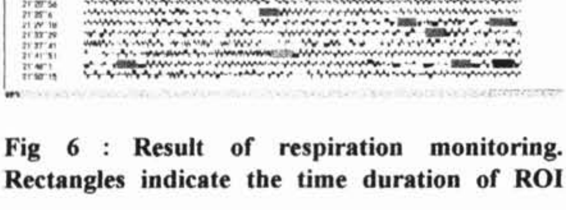

Fig 6 : Result of respiration monitoring. Rectangles indicate the time duration of ROI setting or existence detection. The data that appear on this window were taken for 2 hours.

7 Conclusion

This paper presented the three algorithms for enhancements of the respiration monitoring system. These are *adaptive interval setting*, *adaptive threshold setting*, and *time averaging of image data*.

The time averaging of image data reduces the effects of salt and pepper noises so that even in the darkness of gray levels smaller than about 10, frequency characteristics are still recognized. Small maxima on the graph of respiration patterns or maxima on both sides of a large minimum are not ignored for respiration counting by adaptive threshold setting. The adaptive interval setting makes the respiration patterns conspicuous so that respiration patterns are easily obtained.

We experimentally proved that the improvements in accuracy of respiration pattern detection on the respiration monitoring system led to acquiring more accurate results for respiration counting compared with the previous system.

Future extensions include monitoring other physiological movements such as heartbeats.

Acknowledgements

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