BREATH AND POSITION MONITORING DURING SLEEPING WITH A DEPTH CAMERA

Meng-Chieh Yu[1], Huan Wu[2], Jia-Ling Liou[2], Ming-Sui Lee[1,2] and Yi-Ping Hung[1,2]
[1]*Graduate Institute of Networking and Multimedia, National Taiwan University, Roosevelt Road, Taipei, Taiwan*

[2]*Department of Computer Science and Information Engineering, National Taiwan University, Roosevelt Road, Taipei, Taiwan*

Keywords: Non-contact breath measurement, Sleep monitoring, Sleep position, Sleep cycle, Depth camera.

Abstract: Sleep monitoring is increasingly seen as a common and important issue. In this paper, a depth analysis technique was developed to monitor user's sleep conditions without any physical contact. In this research, a cross-section method was proposed to detect user's head and torso from the depth images. Then, the system can monitor user's breathing rate, sleep position, and sleep cycle. In order to evaluate the measurement accuracy of this system, two experiments were conducted. In the first experiment, eight participants with various body shapes were asked to join the experiment. They were asked to change the sleep positions (supine and side-lying) every fifteen breathing cycles in two circumstances (sleep with and without a thin quilt) on the bed. The experimental results showed that the system is promising to detect the head and torso with various sleeping postures. In the second experiment, a realistic over-night sleep monitoring experiment was conducted. The experimental results demonstrated that this system is promising to monitor the sleep conditions in realistic sleep conditions. To conclude, this study is important for providing a non-contact technology to detect multiple sleep conditions and assist users in better understanding of their sleep quality.

1 INTRODUCTION

Sleep is essential for a person's mental and physical health. Studies indicate that sleep plays a critical role in immune function (Born et al., 1997), metabolism and endocrine function (Spiegel et al., 1999), memory, learning (Maquet, 2001), and other vital functions. However, there are some sleep disorders, such as sleep apnea, insomnia, hypersomnia, circadian rhythm disorders, which might interfere with physical, mental and emotional functioning. For better understanding of sleep problems, many sleep centres and research groups are devoted to the sleep study. Polysomnography (PSG) is a multi-parametric test used in the study of sleep and as a diagnostic tool in sleep medicine. It monitors body functions including brain activity (EEG), eye movement, muscle activity, heart rhythm, and breathing while sleeping (Douglas, et al., 1992). In this study, we focus on the research issues in sleep cycle, sleep breathing, and sleep positions. For the measurement of sleep cycle, EEG monitoring is one of the most accurate methods to detect the period of non-rapid eye movement (NREM) and rapid eye movement (REM). However, it is not convenient to use. In recent years, motion sensor and pressure sensor array are widely used to monitor user's sleep conditions and body movement while sleeping (Actiwatch, 1998; Fitbit, 2010; WakeMate, 2010), as well as estimate the sleep cycle and evaluate the sleep quality. For breath measurement while sleeping, sleep apnea is one of the most important sleep disorder characterized by abnormal pauses in breathing or instances of abnormally low breathing during sleep. For decades, the breath measurement methods would direct contact to the user while monitoring, and it might interfere with the user and reduce the sleep quality. Although some non-contact breath measurement methods were proposed in recent years, such as ultra-wideband (UWB) and structured light plethysmography (SLP), there still have some measurement limitations. For sleep position, in order to prevent sleep apnea, studies showed that side-lying position is the best sleep posture for individuals with sleep apnea (Cartwright et al., 1984; Szollosi et al., 2002; Loord et al., 2007;

Yu M., Wu H., Liou J., Lee M. and Hung Y..
BREATH AND POSITION MONITORING DURING SLEEPING WITH A DEPTH CAMERA.
DOI: 10.5220/0003702000120022
In *Proceedings of the International Conference on Health Informatics* (HEALTHINF-2012), pages 12-22
ISBN: 978-989-8425-88-1

Hoque et al., 2010). A study analysed six common sleep positions, and concluded that supine positions were more likely to lead to snoring and a bad night's sleep (Idzikowski et al., 2003). However, to date, there has been relatively little research conducted on the measurement of sleep positions.

In this study, a sleep monitoring system using a depth camera was proposed to monitor users' breathing rate, body movement, and sleep position in bed. Moreover, we evaluated the measurement accuracy of the system, including the accuracy of head and torso detection, breath measurement (compared to RIP), and sleep movement (compared to Actigraphy). Through the experimental results, we confirmed that the system could accurately monitor user's sleep conditions. This paper is structured as follows: The first section deals with the introduction of present sleep studies. The second section of the article is a review of several breath measurement methods and activity monitoring while sleeping. The proposed system design is described in the third section. The experimental results are demonstrated in section four followed by the discussion on some important findings. Finally, conclusions and suggestions are given for further research.

2 RELATED WORKS

In this section, we discuss relevant literatures of breath measurement and sleep cycle monitoring while sleeping.

2.1 Breath Measurement while Sleeping

Breathing is important while sleeping. There are many breathing-related sleep disorders, such as apnea and hyperventilation syndrome (HVS). Currently, many methods are proposed to monitor the breath conditions while sleeping. Most screening tools consist of an airflow measuring device, a blood oxygen monitoring device, and the respiratory inductance plethysmography (RIP). Thermistor (TH) measurements have been traditionally used to determine airflow during PSG studies. It is placed over the nose and mouth and infers airflow by sensing differences in the temperature of the warmer expired air and the cooler inhaled ambient air. However, low accuracy in detecting hypopneas is a major drawback (BaHamman, 2004). The pulse oximeter is a medical device that monitors the oxygen saturation of user's blood, and changes in blood volume in the skin. Low oxygen levels in the blood often occur with sleep apnea and other respiratory problems (Douglas, et al., 1992). Respiratory Inductance Plethysmography (RIP) measures the body movement of chest wall or abdominal wall caused by breathing exercise (Whyte et al., 1991; Cantineau et al., 1992), and then the breathing conditions can be estimated accurately. However, most of the breath measurement methods are essential to directly contact to the user while measuring, and it might affect the user and decrease the sleep quality.

In recent years, some non-contact breath measurement methods are developed. A study used a CCD video camera to detect the optical flow of the user in bed (Nakajima et al., 2001). PneumaCare developed a non-invasive method called Structured Light Plethysmography (SLP), which utilizes the distortion with movement of a structured pattern of light to calculate a volume or change in volume of a textured surface. Another study conducted an experiment and the results showed that SLP was comparable in performance to spirometer (Wareham et al., 2009). Moreover, slit lights projection (Aoki et al., 2006) is another non-invasive method which measures the breathing conditions by projecting the near-infrared multiple slit-light patterns on the user and measuring the breathing status.

In addition to computer vision-based methods, there is a non-contact method which uses ultra wideband (UWB) to measure the breathing status. A study proposed an application of UWB radar-based heart and breathing activities for intensive care units and conventional hospital beds (Staderini, 2002). Another study used UWB to measure baby's breathing and heart rate especially in terms of opportune apnea detection and sudden infant death syndrome prevention (Ziganshin et al., 2010).

2.2 Sleep Cycle

For monitoring the sleep activity through movement, actigraphy has been used to study the sleep patterns for over 20 years. Actigraphy is a non-invasive method of monitoring human activity cycles (Sadeh, et al., 1994). It is useful for determining sleep patterns and circadian rhythms. The advantage of actigraphy over traditional PSG is that actigraphy can conveniently record the sleep activity (Ancoli-Israel et al., 2003). In recent years, many commercial products were developed, such as Fitbit, WakeMate, and Actiwatch. In general, these products detect the information of time to fall asleep, time to wake up, and totally sleeping time. A study evaluated the measurement results of actigraphy and compared to PSG, and the experimental results showed that sleep parameters from actigraphy corresponded reasonably well to PSG (Kushida et al., 2001). In addition, there is a non-contact method which uses a microphone and an infrared sensor to monitor the sleep status. Moreover, some studies utilize motion sensors (accelerometer, piezoelectric sensor) inside the pillow (Harada et al., 2000) or bed (Malakuti et al., 2010; Hoque et al., 2010) to monitor the sleep movement and sleep positions.

However, none of related research in our survey has a complete study to provide a non-contact and multi-functioning sleep monitoring technique to monitor the sleep conditions. In this study, we developed a non-contact sleep monitoring system which can monitor user's sleep position, breathing condition, and body movement in the same time.

3 SYSTEM DESIGN

In this study, a cross-section object detection method is proposed to detect user's head and torso using a depth camera. The sleep position, body movement, and breathing condition are monitored once the head and torso is detected. The procedure of this method is as follows: First, the view transformation is estimated. Then, a median filter is adopted to reduce the image noise after view transformation. Next, a cross-section method is used to detect user's head and torso so that the sleep position and body movement can be measured. Besides, a breath measurement method is proposed to detect the breathing conditions through the movement of the torso. The system framework of this system is shown in Figure 1.

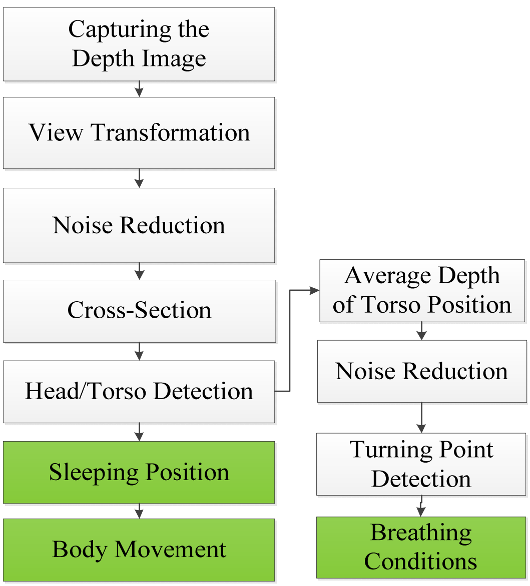

Figure 1: System Framework.

3.1 System Environment

In this system, a depth camera (Microsoft, 2011) is used to capture the sequence of depth images of the user on the bed. The depth camera consists of an infrared laser projector combined with a CMOS sensor, which captures color images and a depth images under ambient light condition. In addition, the depth image can also be captured under the no-light condition. For the reason of easy setup and preventing the interference with the sight view of the user while sleeping, in this study, the depth camera is placed on the wall behind the head instead of suspending from the ceiling. Besides, in order to ensure that the user's head and torso can be captured, and for the issues of breath measurement distance (the shorter the better), the limitation of sensing distance (larger than 0.8m), the depth camera is placed in the distance of 125 cm (49.2 inches) from the bed. The diagram for the system is shown in Figure 2. The region between gray dotted lines indicates the sight view of the depth camera, and the region between yellow lines indicates the sight view of the user.

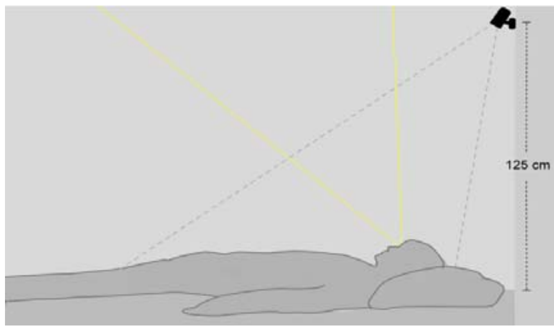

Figure 2: System Diagram.

3.2 Depth Image Processing

Although the skeleton of the user body can be extracted easily through Microsoft Kinect SDK, the skeleton of body while lying on the bed cannot be extracted easily. It is because that the background is too close to the user, and the body might be covered by a quilt. In this study, a cross-section method is proposed to detect user's head and torso with a depth camera. We process the depth image signals at the resolution of 320 pixels in width and 240 pixels in height, and the frame rate is 30 frames per second.

View Transformation

In order to determine the cross-sections of the depth image, we would like to transform the camera view from the side view to the top view. To do that, we need to calculate bed's normal vector first. In order to rotate the camera view to the top of the bed, three points and one rotate center point need to be specified manually. After taking three 3D-points on the bed and using cross product, the system could get the normal vector of the bed. Then, these 2D-points could project to 3D-points in the real world. Then, we proceed to calculate rotation matrix for the bed's normal vector. Once we have the rotation matrix, we can project all 2D points back to 3D point-cloud. Again, we project it back to 2D depth image. However, it will lose some information after rotating the camera view, so a median filter is used to fill empty holes. Figure 4b shows the original depth image, and Figure 4c shows the depth image after view transformation.

Cross-Section Method

We generate several binary images by setting different thresholds starts from the shallowest point of the depth image to the depth of the bed. We generate cross-sections every 2 cm (0.787 inches) from top to bottom. Generally, the distance between the highest point of the human body and the bed is around 18~28 cm, therefore, there would be 9~13 transverse sections of the person from top to bottom. Figure 3 shows ten cross-sections (red line) from the highest point of the red point to the bed.

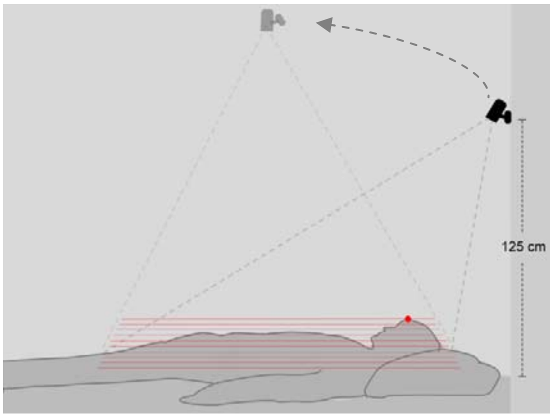

Figure 3: Cross-sections of the lying user from top to bottom. Red point indicates the highest point of the user.

Head and Torso Detection

By using connect-component analysis, the components from each cross-section can be extracted. The concept of this method is to find out spheres in each cross-section. Once there is a circle growing larger from top section to bottom section, we assume that it might be a sphere there. So far, this algorithm might find other spheres. To decide the highest sphere, we collect each circle's contribution from each section. More circles at the same location means higher probability to have sphere there. If sphere candidates have n different locations, the probability that might be a sphere at location l is:

$$P(l) = \frac{\sum^{sections} \# \; of \; circles \; at \; l}{\sum_{i=0}^{n} \sum^{sections} \# \; of \; circles \; at \; i} \tag{1}$$

In addition to detecting head from single depth image, we need to leverage the advantage of video sequence. Hence, we push every head location found by each frame into a queue. Then, we use the same idea to re-locate the highest probability head-like sphere. This will avoid some occasional misleading failed detection.

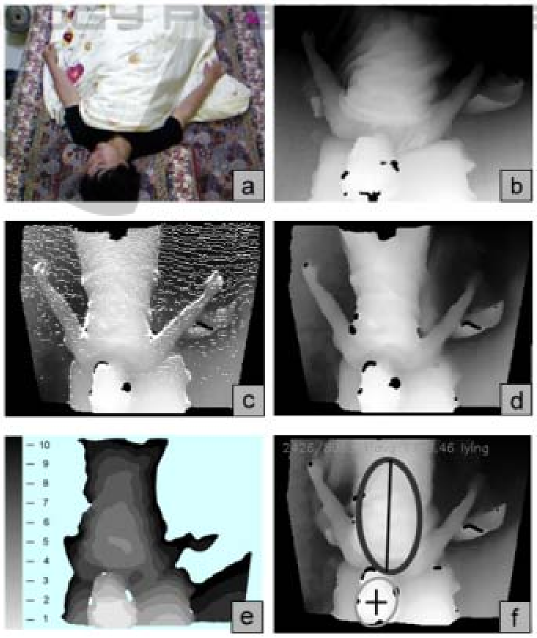

Figure 4: Depth image Processing Procedure of our system. (a) Captured color image. (b) Captured depth image. (c) View transformed image. (d) Filtered image. (e) Cross-section image. (f) Final result of head/torso detection.

Once the head is detected, the next step is to detect the torso's ROI (region-of-interest). We adopt almost the same way as detecting the head, but this time we track cuboids rather than spheres. However, there is a problem that the pillow might be recognized as a torso. Therefore, we reject cuboids if there is a head on it. Figure 4 shows the processing procedure of head and torso detection in this system.

Head and Torso Detection Algorithm

Inputs:
C := Set of circles from each sections
Cu := Set of cuboid from each sections
Th := threshold distance to determine two different cluster

Outputs:
Head and torso positions

Steps:
1.Classify_components(C,Th)
{
//Classify C into clusters according to distance Th.
1.1 clusters_num = SeqPartition(C,Th)

1.2 voting[cluster_num] //# of member in each component
1.3 leader[cluster_num] //the biggest sphere size in individual cluster
1.4 if(clusters_num > 0)
{
1.4.1 Loop for each C_i element in C
1.4.1.1 num = cluster_number(i)
1.4.1.2 if(voting[num] == 0 OR leader[num]'s size < Ci's size)
leader[num] = C_i
End if
1.4.1.3 voting[num] = voting[num] + 1
1.4.2 End loop
1.5 }
1.6 Sort voting and leader array
1.7 Return array and # of cluster
}

2. Q_{head} := a queue that collects head's position and location in the video sequence.

Find_head(C)
{
2.1 Th = head_boundary.
2.2 Head = Classify_components(C,Th).
2.3 Push Head into queue Q_{head}.
2.4 Final_Head = Classify_components(Q_{head},Th).
}

3. Q_{torso} := a queue that collects torso's position and location in the video sequence.
Find_torso(Cu,Head)
{
3.1 Th = torso_bounday
3.2 Remove cuboid from Cu if it intersects with Head.
3.3 Torso = Classify_ components(Cu,Th).
3.4 Push Torso into queue Q_{torso}
3.5 Remove cuboid from Q if it intersects with Head.
3.6 Final_torso = Classify_ components(Q_{torso},Th).
}
4. Detect_body()
{
4.1 Collect C and Cu from each sections
4.2 if (Head = Find_head(C))
4.2.1 Torso = Find_torso(Cu)
4.3 End if
}

Breath Measurement

The breathing signal can be extracted from the torso ROI once we detect the head and torso. While the user is inhaling, his chest wall will expand, and the average depth value of the torso ROI will decrease; on the contrary, the average depth value of the torso ROI will increases while the user is exhaling. Therefore, the sequential of the average depth value of the torso ROI is considered as the breathing signal under the premise that the user is sleeping. For breath measurement, a turning point detection algorithm is proposed. At first, a mean filter is used for reducing the noises caused by the sensing deviation and body movements. Then, the turning points of the breathing signal are detected using the second derivative method. Finally, in order to eliminate redundant turning points, a dynamic threshold is applied to find the exact peak points and valley points. Figure 5 shows a fragment of the breathing signal (blue line) and the measurement results (vertical gray line) during a realistic overnight sleep.

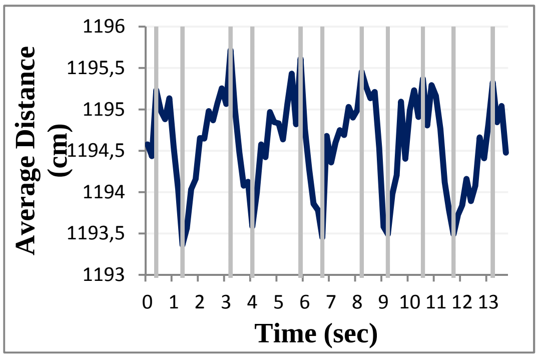

Figure 5: Breath Measurement. The blue line indicates the raw breathing signals, and the gray lines indicate the turning points which we detected.

While the turning points of the breathing signals are detected, the information of the breathing conditions can be figured out easily. The breathing conditions include the breathing rate, breathing depth, breathing stability, inhalation time, exhalation time, inhalation/exhalation ratio, and sleep apnea symptoms.

Body Movement

The body movement is defined as the sum of head movement and torso movement. The HR_t indicates the average depth value of the head ROI in time t, and the TR_t indicates the average depth value of the head ROI in time t. Then, the absolute difference value between two adjacent images frames could be calculated (Equation 2). M_t indicates the movement value of the user in time t.

$$M_t = |HR_t - HR_{t-1}| + |TR_t - TR_{t-1}| \quad (2)$$

Sleep Position

In this system, two main sleep positions (supine position and side-lying position) can be recognized. After the head and torso are detected, the highest point of head ROI and torso ROI can be found. Then, the ratio of the highest head point to torso point is calculated. Figure 6 shows the highest point of head ROI (blue dot) and torso ROI (red dot) in the side-lying position and supine position.

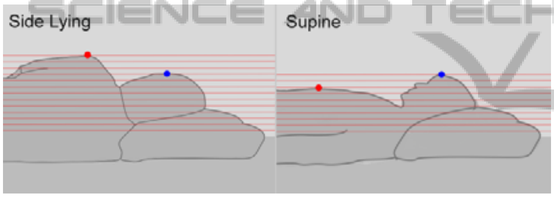

Figure 6: Sleep Positions. Red dot indicates the highest point of torso ROI, and blue dot indicates the highest point of head ROI.

Next, the sleep position can be classified according to the ratio defined in equation 3. In order to find out the threshold to classify the sleep position, an experiment was conducted to record five participant's (two females and three males) highest points of head ROI and torso ROI in two sleep positions (side-lying and supine) and two conditions (sleep with no quilt and sleep with a thin quilt) (Figure 7). The results revealed that the distance of the highest head point does not change significantly in different sleep positions and conditions. However, the distance of the highest torso point changed significantly in different sleep positions. The average ratio is -0.02633 in supine position, and it is 0.0652 in side-lying position. Therefore, the detection threshold of sleep position is set to the median value: 0.01. While the ratio is larger than the threshold value, the sleep position is defined as the supine position. Otherwise the sleep position is defined as the side-lying position (equation 4). From Figure 7, we can observe that the standard deviation of the body distance is bigger in side-lying position than others. It is because the highest torso points are different for female and male. However, our method can also distinguish the sleep position accurately no matter no matter the gender.

$$Ratio = \frac{D_{head} - D_{torso}}{D_{head}} \quad (3)$$

$$Posture = \begin{cases} Side\ lying & if\ \ Ratio > 0.01 \\ Supine & Otherwise \end{cases} \quad (4)$$

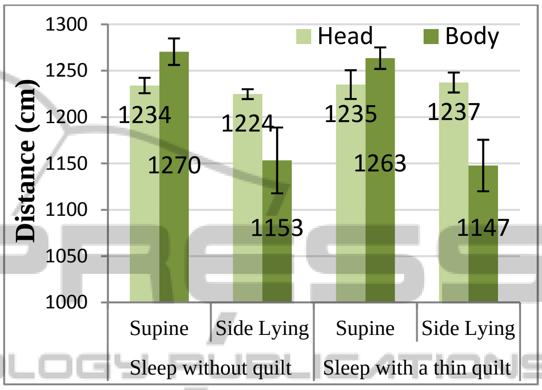

Figure 7: The distance between the depth camera and the highest point of head ROI and torso ROI in two positions (supine and side-lying) and two conditions (sleep with no quilt and sleep with a thin quilt).

3.3 Measurement Limitations

There are some measurement limitations in this system. First, according to the law of rectilinear propagation of light, the depth value cannot be detected while the IR patterns are blocked by objects. From the experiment results, we found that the most common problem is that the hand would block some of the depth IR patterns while side-lying. It might affect the accuracy of torso detection. Second, the breathing amplitude of torso movement would be decreased with the increase of the thickness of quilt. According to our test, the average breathing amplitude of the torso movement with no quilt is 0.5 cm and it is 0.35 cm while sleeping with a thin quilt. The thickness of the thin quilt in our test is 0.6 cm. However, while sleeping with a thick quilt, such as thick silk-padding quilts, the system might not accurately detect the torso movement caused by breathing exercise.

4 EXPERIMENTS

Two experiments were conducted to evaluate the measurement accuracy of head/torso detection, sleep position, body movement, and breath measurement of this system. First experiment was mainly designed to evaluate the measurement reliability for different users. Second experiment was designed to evaluate the measurement accuracy in realistic overnight-sleep condition.

4.1 Experiment I

Experimental Design

Eight participants volunteered to participate in this experiment (five males and three females). The average age is 33.8 years old (SD = 17.6), including two sixty-year old participants, five young participants (25~30 years old), and a ten-year old participant. The body mass index (BMI) of them is in the range between 18.6~29.75. In this experiment, participants were asked to lie down on the pillow, and a breathing sensor, RIP (Thought Technology Ltd., 2010), was used to record the breathing conditions as the ground truth. During the experimental procedure, they were asked to change the sleep position every fifteen breathing cycles. The procedure of this experiment is in the sequence of supine, lying on the right side, supine, lying on the left side, supine, and lying on the right side. Totally, the participant needed to change the sleep position five times. Besides, the experimental procedure needed to be done twice, including a condition that the participants sleep with a thin quilt, and a condition that they sleep with no quilt. Before each task, participants were reminded not to breathe deliberately.

Experimental Results

The sleep measurement were divided into four different conditions in this experiment, including two sleep positions (side-lying and supine) and two circumstances (sleep with a thin quilt and sleep with no quilt). For each condition, the total numbers of correct head detection frames were calculated manually as well as the total numbers of correct torso detection frames. The average of accurate rate and standard deviation in each condition are listed below. The experimental results showed that while participants slept with no quilt, the measurement accuracy of head detection was 98% (SD = 0.036) while in the side-lying position, and it was 99.3% (SD = 0.018) in the supine position. Moreover, the measurement accuracy of torso detection was 91.5% (SD = 0.16) in the side-lying position, and it was 99.3% (SD = 0.01) in the supine position. Besides, while participants slept with a thin quilt, the measurement accuracy of head detection is 96.7% (SD = 0.11) in the side-lying position, and it was 99.5% (SD = 0.02) in the supine position. Moreover, the measurement accuracy of torso detection was 94.5% (SD = 0.1) in the side-lying position, and it was 99.5% (SD = 0.008) in the supine position. Overall, the average accurate rate was 98.4% in head detection and 96.4% in torso detection. The experimental results of head and torso detection are shown in Figure 8.

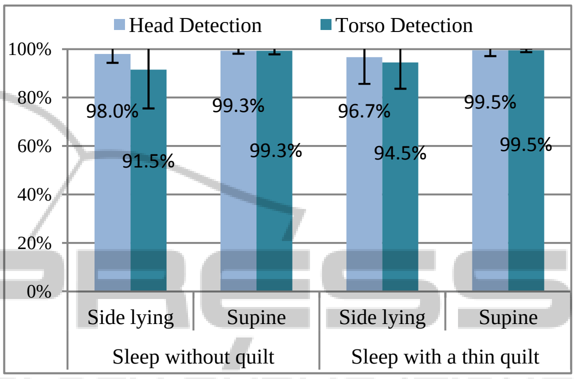

Figure 8: Measurement results of head and torso detection in experiment I.

For breath measurement, the measurement accuracy is defined as the ratio of the totally breathing cycles we detected to the totally breathing cycles the RIP system detected. The measurement results of the RIP system was regarded as the ground truth of the breathing conditions. The experimental results show that while the user sleeps with no quilt, the measurement accuracy of breathing rate was 81.9% (SD = 0.11) in the side-lying position, and it was 90.4% (SD = 0.07) in the supine position. Moreover, while the user sleeps with a thin quilt, the measurement accuracy of breathing rate was 84.1% (SD = 0.05) in the side-lying position, and it was 88% (SD = 0.08) in the supine position. Overall, the

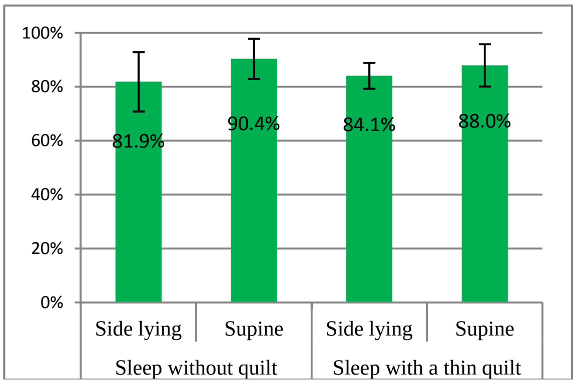

Figure 9: Measurement results of breath measurement in experiment I.

average accurate rate of breath measurement was 86.3%. The experimental results of the breath measurement are shown in Figure 9.

For sleep position, the experimental results showed that in the circumstance of sleeping with a thin quilt, the detection accuracy was 100% (N=24) in the side-lying position, and it was 100% (N=24) in the supine position. Besides, while the user slept with no quilt, the detection accuracy was 95.8% (N=24) in the side-lying position, and it was 100% (N=24) in the supine position.

4.2 Experiment I I: Realistic Overnight-Sleep Monitoring

Experimental Design

The experiment was conducted to ensure that the system could monitor the realistic overnight-sleep conditions accurately. A male participant (28 years-old) volunteered to participate in this experiment. The same as the first experiment, the breathing sensor (RIP) was used to measure the breathing conditions as the ground truth. In addition, an actigraphy was used to measure the movement of the non-dominant hand while sleeping (Figure 10). There was only one limitation that the participant was asked to lie on the pillow. In this experiment, the participant was asked to participate in a ten-day overnight-sleep monitoring experiment. The experiment did not specify the time to go to the bed, the time to getting up, and the totally sleeping time. Besides, we required participants to sleep with a thin quilt for five days, and to sleep with no quilt for another five days. Participant's breathing rate, body movement, and sleep position were monitored by our method and compared to the RIP and actigraphy. Figure 11 shows one of a realistic overnight-sleep monitoring results in day 3. Figure 11a shows the measurement results of breathing rate. Red curve indicates the measurement results of RIP system, and the blue curve indicates the measurement results of our system. Lower part of Figure 11a shows the

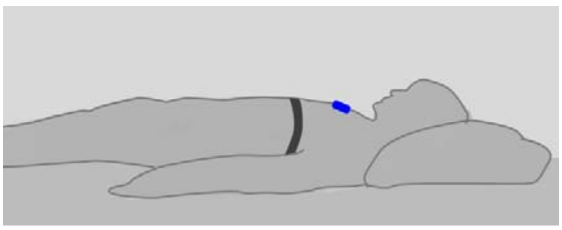

Figure 10: Experimental Diagram. The breathing sensor (RIP) and actigraphy are used to detect the breathing rate and body movement.

sleep positions we detected (blue) and real condition (red). Figure 11b shows the movement level detected by an actigraphy, and Figure 11c shows the movement level detected by our system. In this day, the participant slept with a thin quilt from 1:30 AM to 4:53 AM.

Experimental Results

The same with experiment I, the sleep measurement were divided into four different conditions, including two sleep positions (side-lying and supine) and two sleep circumstances (sleep with a thin quilt and sleep with no quilt). Totally, the participant slept 42 hours in ten nights.

Following shows the experimental results. In the circumstance of sleeping with no quilt, the measurement accuracy of head detection was 89.4% (SD = 0.14) in the side-lying position and it was 99.9% (SD = 0.0007) in the supine position. Moreover, the measurement accuracy of torso detection was 89.3% (SD = 0.014) in the side-lying position and it was 89.3% (SD = 0.0003) in the supine position. Besides, in the circumstance of sleeping with a thin quilt, the measurement accuracy of head detection was 99.9% (SD = 0.007) in the side-lying position and it was 98.8% (SD = 0.17) in the supine position. Moreover, the measurement accuracy of torso detection is 99.4% (SD = 0.0003) in the side-lying position and it is 99.9% (SD = 0.003) in the supine position. The experimental results of head and torso detection are shown in Figure 12. Overall, the average accurate rate of head detection was 96.7% (SD = 0.073), and the average accurate rate of torso detection was 96.8% (SD = 0.031).

For body movement, the times of the movement events in our method and actigraphy were compared. According to the observation, we observed that big body movement can be measured both in our system and actigraphy, such as the event of turning over the body. Besides, micro-movement could be measured, (see Figure 11b and 11c).

For breath measurement, the measurement accuracy of breathing rate was 89.7% (SD = 0.05) in the side-lying position and it was 92.8% (SD = 0.05) in the supine position in the circumstance of sleeping with no quilt Moreover, the measurement accuracy of breathing rate was 92.4% (SD = 0.07) in the side-lying position, and it was 92.7% (SD = 0.07) in the supine position. Overall, the average accurate rate of breath measurement was 92.03% (SD = 0.044). The comparison of the breath measurement in these different conditions is shown in Figure 13.

For sleep position, the experimental results showed that in the circumstance of sleeping with a

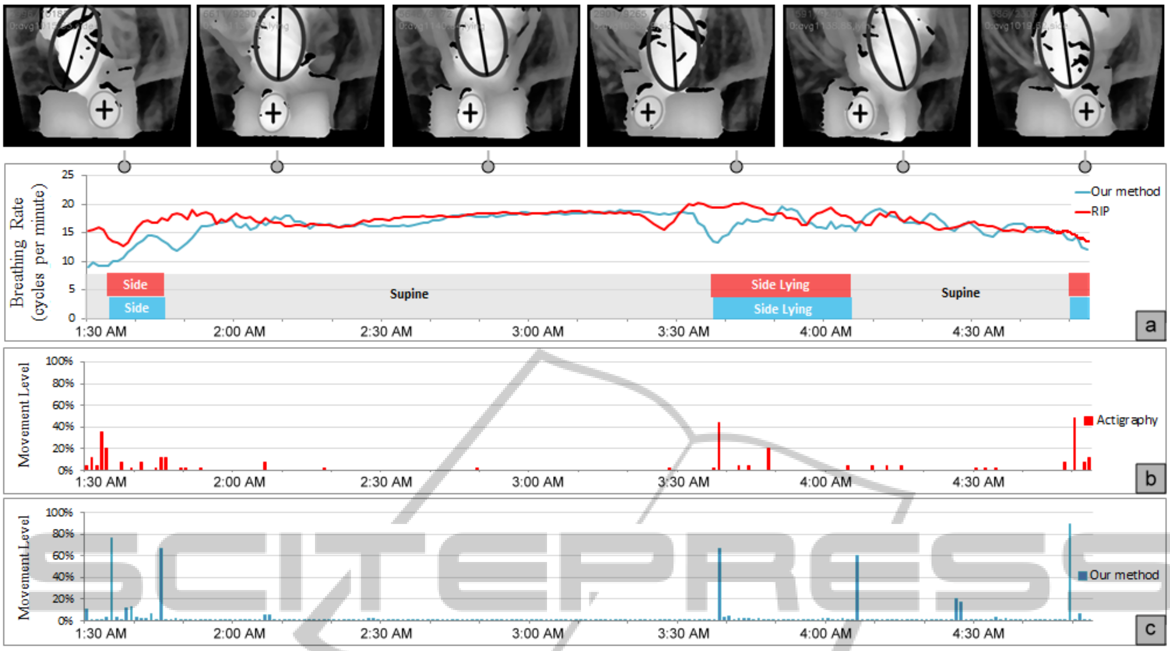

Figure 11: A Realistic Overnight-Sleep Monitoring. Red color indicates the ground truth measured by RIP and actigraphy, and the blue color indicates the results of our system. (a) The results of breathing rate and sleep positions. (b) The movement level detected by an actigraphy. (c) The movement level detected by our system.

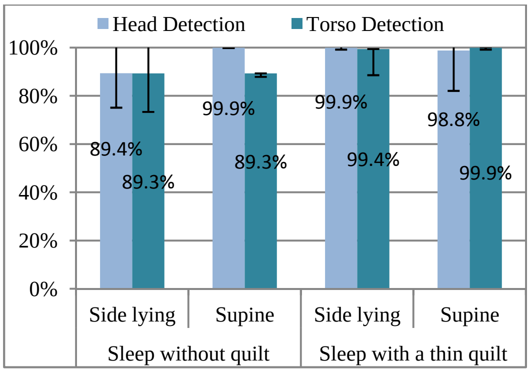

Figure 12: Measurement results of head and torso detection in experiment II.

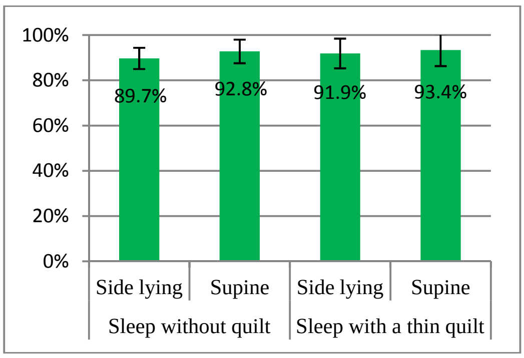

Figure 13: Measurement results of breath measurement in experiment II.

thin quilt, the detection accuracy was 94.7% (N=19) in the side-lying position, and it was 100% (N=21) in the supine position. Besides, while the user slept with no quilt, the detection accuracy was 88.23% (N=17) in the side-lying position, and it was 100% (N=20) in the supine position.

5 DISCUSSIONS

The aim of this section is to summarize, analyse and discuss the results of experiments and give guidelines for the future developments.

5.1 Head/Torso Detection

From the experimental results of head and torso detection, we observed some issues worthy of discussion. First, while the user slept with a thin quilt, the overall detection accuracy of torso was better than uncovered. One reason might be that the thin quilt could smooth the shape of the torso, and enhance the measurement accuracy. Second, we found that the gesture might affect the head detection. In this system, the head and torso could be detected accurately under the premise that the shape of the head or torso is not overlapped by hand or other objects. Figure 14a and 15b show two special sleep gestures that can be detected accurately. It is because that the shape of the head is not overlapped. However, there are some conditions that the head or torso could not be detected well. According to the observation, we found that the head could not be detected well while the user is scratching (Figure 14c and d). In this condition, the shape of the head might be changed and no longer a sphere contour. In this case, the system could not recognize it as a head. One possible solution method is to detect the hand position, and then we can estimate the head position while the head is overlapping by hand.

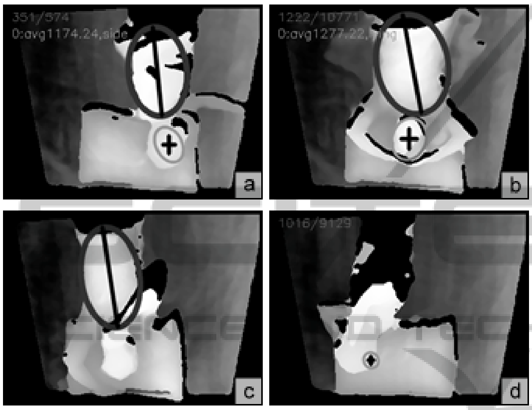

Figure 14: Special Sleep Postures.

In addition, there are some sleep conditions or sleep positions that we did not discuss. First, the algorithm of head and torso detection we proposed can be applied to detect multiple heads and torsos. Moreover, a shortest distance pairing procedure is used to pair the head and torso of specified sleeper. However, we still have the detection problem while the users are overlapping. Second, the head and torso can be detect in the prone position. Howerer, this system can not recogize whether the user is in the supine position or prone position now. Figure 15 shows the detection result of the head and torso detection in the prone position and multiple users.

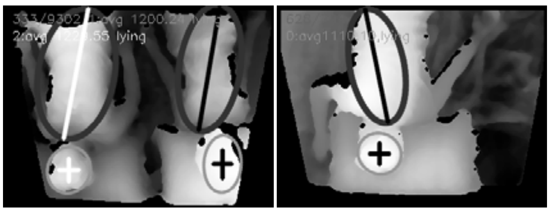

Figure 15: Other Sleep Conditions. Left: multiple sleepers. Right: prone position.

5.2 Breath Measurement

From the experimental results of breath measurement, we observed some phenomenon which was similar to the conditions of head and torso detection. First, the measurement accuracy of breathing is higher while sleeping in the supine position than in the side-lying position. We observed that there are more noises in the side-lying position than in the supine position. Besides, according to our measurement results, the average amplitude of the breathing signals is 0.8 cm in the supine position. However, the average amplitude of the breathing signals is about 0.5 cm in the side-lying position. Overall, less signal noises and more breathing amplitude would increase the measurement accuracy while sleeping in the supine position. Second, the overall measurement accuracy of breathing while sleeping with a thin quilt was better than the accuracy while sleeping with no quilt. We speculate that it might because the reason that the thin quilt reduces the wrinkles of the torso surface. Third, the movement of the torso is seen as the breathing signal, but the system cannot identify whether the movement is caused by breathing exercise or other exercises. According to the observations of the measurement results in experiment I, we found that there were more detection errors while the user is moving or turning around in bed. In experiment I, the participants were asked to turn over the body frequently, and the participant was almost in static condition in experiment II. That’s the reason that the measurement accuracy of breathing is lower in experiment I than in experiment II. One possible solution method is to suspend the breathing measurement while the user is moving.

6 CONCLUSIONS AND FUTURE WORK

In this study, we proposed a depth image sequence analysis technique to monitor user’s sleep position, body movement, and breathing rate on the bed without any physical contact. A depth image-based processing method is proposed to monitor the sleeping conditions. The results of experimental I showed that the proposed method is promising to detect the head and torso with various sleeping postures and body shapes. The results of experimental II showed that the system can accurately monitor the sleeping conditions. Therefore, we confirm that the system could provide relevant sleep information and sleep report to the user. Furthermore, the sleep parameters which we detected can provide to the sleep centre to diagnose the sleep problems. This study is important for providing a non-contact technology to measure the sleep conditions and assist users in better understanding of his sleep quality.

In the future, we expect to detect more sleeping conditions and solve some measurement limitations, such as the problems of overlapping. Besides, we will develop a multimedia feedback sleep-assisted system which can detect the breathing status and provide appropriate sleeping guidance in real time to help users shorten the time to fall asleep. In addition, a web-based browser will be developed to provide the personalized sleeping information to the user.

ACKNOWLEDGEMENTS

This work was supported by the National Science Council, Taiwan, under grants NSC 98-2221-E-002-127-MY3. And many thanks to HealthConn Corp. (http://hcc.healthconn.com/), who provided many assistances of the professional knowledge.

REFERENCES

Aoki, H. and Koshiji, K., 2006. Non-contact Respiration monitoring method for screening sleep respiratory disturbance using slit light pattern projection. *World Congress on Medical Physics and Biomedical Engineering, 14(7)*, 680-683.

Ancoli-Israel, S., Cole, R., Alessi, C., Chambers, M., Moorcroft, W., Pollak, C. P., 2003. The role of actigraphy in the study of sleep and circadian rhythms, *Sleep , 26(3)*, 342-392.

BaHammam, A., 2004. Comparison of nasal prong pressure and thermistor measurements for detecting respiratory events during sleep. *Respiration, 71(4)*, 385-390.

Idzikowski, C., 2003. Sleep position gives personality clue. BBC News, 16 September 2003.

Born, J., Lange, T., Hansen, K., Molle, M. and Fehm, H. L., 1997. Effects of sleep and circadian rhythm on human circulating immune cells. *The Journal of Immunology, 158(9)*, 4454-4464.

Cantineau, J. P., Escourrou, P., Sartene, R., Gaultier, C., and Goldman, M., 1992. Accuracy of respiratory inductive plethysmography during wakefulness and sleep in patients with obstructive sleep apnea. *Chest, 102(4)*, 1145-1151.

Cartwright, R. D., 1984. Effect of sleep position on sleep apnea severit. *Sleep, 7(2)*, 110-114.

Douglas, N., Thomas, S., and Jan, M., 1992. Clinical value of polysomnography, *Lancet, 339*, 347-350.

Fitbit, http://www.fitbit.com/ , retrieved on 2011/5.

Harada, T., Sakata, A., Mori, T., and Sato, T., 2000. Sensor pillow system: monitoring respiration and body movement in sleep, *Intelligent Robots and Systems*, 1, pp. 351-356.

Hoque, E., Dickerson, R. F., Stankovic, J. A., 2010. Monitoring body positions and movements during sleep using WISPs. *Wireless Health*, 44-53.

Kushida, C. A., Chang, A., Gadkary, C., Guilleminault, C., Carrillo, O., and Dement, W.C., 2001. Comparison of actigraphic, polysomnographic, and subjective assessment of sleep parameters in sleep-disordered patients. *Sleep Med., 2(5)*, 389-396.

Microsoft, Kinect, http://www.xbox.com/kinect, retrieved on 2011/3.

Loord, H., and Hultcrantz, E., 2007. Positioner - a method for preventing sleep apnea. *Acta Oto-laryngologica, 127(8)*, 861-868.

Maquet, P., 2001. The role of sleep in learning and memory. *Science, 294*, 1048–1052.

Malakuti, K. and Albu, A. B., 2010. Towards an intelligent bed sensor: Non-intrusive monitoring of sleep irregularities with computer vision techniques. *International Conference on Pattern Recognition*, 4004-4007.

Nakajima, K., Matsumoto, Y., and Tamura, T., 2001. Development of real-time image sequence analysis for evaluating posture change and respiratory rate of a subject in bed. *PHYSIOLOGICAL MEASUREMENT*, 22, N21-N28.

Philips Actiwatch, http://www.healthcare.philips.com/ , retrieved on 2010/8

PneumaCare, http://www.pneumacare.com/ , retrieved on 2011/6.

Wareham,R., Lasenby,J., Cameron, J., Bridge, P. D., and Iles, R., 2009. Structured light plethysmography (SLP) compared to spirometry: a pilot study, *European Respiratory Society Annual Congress*.

Sadeh, A., Sharkey, K. M., and Carskadon, M. A., 1994. Activity-based sleep-wake identification: an empirical test of methodological issues. *Sleep, 17(3)*, 201-207.

Staderini, E. M., 2002. UWB radars in medicine. *Aerospace and Electronic Systems Magazine, 17(1)*, 13-18.

Spiegel, K., Leproult, R., and Cauter, D. V., 1999. Impact of sleep debt on metabolic and endocrine function. *The LANCET, 354(9188)*, 1435-1439.

Szollosi, I., Roebuck, T., Thompson, B., Naughton, M. T., 2002. Lateral sleeping position reduces severity of central sleep apnea/cheyne-stokes respiration, *Sleep, 29 (8)*, 1045-1051.

Thought Technology Ltd., http://www.thoughttechnology.com/, retrieved on 2010/6.

Wang, C., Ahmed, A., and Hunter, A., 2007. Locating the upper body of covered humans in application to diagnosis of obstructive sleep apnea. *Proceedings of the World Congress on Engineering*, 662-667.

Whyte, K. F., Gugger, M., Gould, G. A., Molloy, J., Wraith, P. K., and Douglas, N. J., 1991. Accuracy of respiratory inductive plethysmograph in measuring tidal volume during sleep, *Journal of Applied Physiology, 71(5)*, 1866-1871.

WakeMate, http://www.wakemate.com/ , retrieved on 2011/5.

Ziganshin, E. G., Numerov, M. A., and Vygolov, S. A., 2010. UWB baby monitor. *Ultrawideband and Ultrashort Impulse Signals*, 159-161.