A Robust Pose Matching Algorithm for Covered Body Analysis for Sleep Apnea

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Abstract— **Existing video monitoring techniques require clinicians to analyze substantial amounts of video data in diagnosis of sleep apnea. Analysis of the covered human body from video is a challenging task as traditional computer vision methods such as correlation, template matching, background subtraction, contour models and related techniques for object tracking become ineffective because of the large degree of occlusion for long periods. In condition of persistent heavy occlusion, difficulties arise from night vision, large variances of image features according to the occlusion level, the shifting of the cover surface with movements, obscuration of the bodies' edges by the cover, and wrinkle noises. We propose a near real time method to robustly estimate the pose of fully/partially covered or uncovered human body. The proposed method contains a novel weak human model to accommodate large variances of image features and a strong pose recognition model derived from a stylized pose detector used for people tracking by Ramanan et al. [10]. We improve the stylized pose detection model by modifying the cost formula and template representation to overcome weak cues and strong noise due to heavy occlusion. In evaluation, the experimental results show that the proposed model is promising to estimate the pose of a human body with fully or partially covered or without covered.**

I. Introduction

Video Monitoring has been adopted to assist diagnosis on obstructive sleep apnea, which results in sleep disturbance and consequential daytime sleepiness, leading to potentially serious consequences for the individual, employers and society as a whole. The apnea often ends with a loud snore or gasp, along with movements of the whole body. Sivan et al.[12] indicate that results from traditional Polysomnography are highly correlated with human observation of video test results. Recognition of covered human body activity appears to be a challenging task. Existing monitoring techniques in the sleep lab[14] utilize motion sensors, patterned sheets and infrared light to compute gross degrees of motion from video recorded throughout the night. However, gross motion suggests only periods of activities rather than identifying what the activities are, which still require clinicians to analyze substantial amounts of video data. Hence, there is a need for more automated methods for covered body analysis.

Human pose estimation in computer vision has been working on the tracking part and proposes various sampling schemes such as mean field Monte Carlo[6] and annealed particle filter[3], while utilizing simple detection models like rectangles of edges or motion. Such methods work well under requirements of clear image cues (for simple detection models) and clean full body motion data (for dynamical models in sampling). However, in real world applications, partial occlusion often occurs and the assumptions to obtain clear image cues and to have clean and complete full body motion often fail. Ramanan et al.[10] indicate that in their experiences low-level image features play a crucial role and their work concentrates on the detection part.

Manuscript received July 5, 2008; revised August 15, 2008

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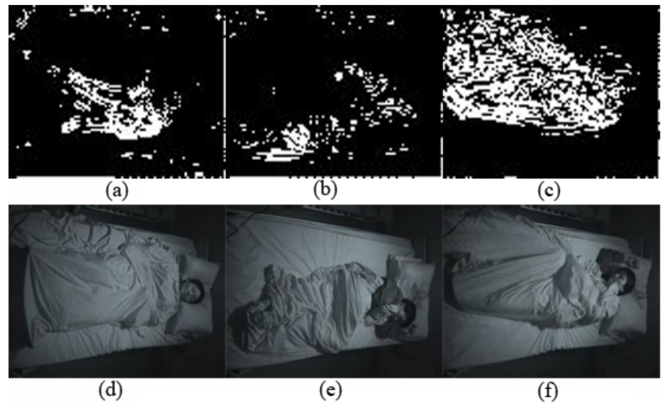

Fig. 1. Obscured and Fragmented Motion (a),(b),(c) with Raw Image of Covered Subjects (d),(e),(f)

Apart from partial occlusion, in real world scenes, it is likely that partial and irregular motion information can be available, which seriously affects the usability of the aforementioned methods. In our application to monitor patients' behavior, the goal is to estimate human poses in conditions of persistent heavy occlusion with casual movements as seen in Fig. 1. Although there is some published research investigating the monitoring of partially occluded humans [5], [11], [13], [19], the methods examined do not deal with pose estimation of consistently and almost wholly occluded subjects.

This research addresses the problem of detecting and segmenting the covered human body using infrared vision. In the targeting problem domain, difficulties arising from night vision, large variances of image features according to the occlusion level, the shifting of the cover surface with movements, obscuration of the bodies' edges by the cover, and wrinkle noises are compounded by human articulated deformation. Traditional computer vision methods such as correlation, template matching, background subtraction, contour models and related techniques for object tracking become ineffective [2], [7] because of the large degree of occlusion for long periods.

II. Proposed Method

People use multiple visual cues to recognize objects, such as the color, texture, silhouette and shape of the object. In the absence of color, texture and silhouette information in our problem domain, the analysis of object recognition can be only based on the geometry alone. The proposed method overcomes the difficulties from poor quality of image cues due to heavy obscuration, from large variance on image features due to unpredictable human behavior to remove or pull back the cover, from poor quality of motion due to heavy obscuration, and from fragmented motion due to partial and occasional movement.

The proposed method is comprised of two models. (1) A robust weak human model to accommodate large variance of image features is introduced in Sec.III. We improve and extend our previous efforts [16], [17] of a covered upper body detection model to locate the obscured head and torso by adding multiple detectors utilizing weak features for individual body part and integrating the decisions of sub-models into a weak human model. (2) A stylized pose matching model to identify the posture of the covered body is described in Sec.IV. The pose recognition model uses multiple human hypotheses generated by the obscured human upper body model as regions of interest, chamfer matches distance transformed maps of individual edge orientation information with pre-trained human templates, and outputs human configurations with the lowest matching cost. The pose recognition model is derived from a stylized pose detector used for people tracking by Ramanan et al.[10]. We improve the stylized pose detection model by modifying the cost formula and template representation to overcome weak cues and strong noise due to heavy occlusion.

In evaluation, we compare our modified stylized pose detection model with the original stylized pose detector and show that the proposed model outperforms the original pose detector, which tends to suffer from strong noise generated by the cover in our problem domain. The experimental results are presented in Sec.V, showing that the proposed model is able to estimate the obscured body pose. Without code optimization, the system runs near to real time (it takes 0.4 second to process a frame with a P4 2.4GHz CPU on average). Limitations of the proposed method and future work are discussed in Sec.V-C. We conclude in Sec.VI.

III. Weak Human Model

The initial set of hypotheses of the head and torso are proposed by the weak human model, which is comprised of a novel obscured head model, a novel obscured shoulder detector, a novel obscured torso model and a novel leg joint detector.

A. Obscured Head Detection

The head detector is used to propose the initial set of human hypotheses. There has been considerable work on face detection in computer vision research over the past ten years. However, most of the face detection systems require at least portions of the face to be shown, such as both eyes and therefore are inapplicable in our problem domain since patients may sleep on their side, presenting only half or less of the face. Therefore, the first contribution of this work is a head detector invariant to facial direction.

The head model weighting function constitutes four sub-weighting functions utilizing various types of features, and measuring the region of interest from different aspects in order to overcome occlusion and obscuration. The multiple head hypotheses obtained with weights greater than zero are then used to search for the torso and further pose estimation.

The weighting function of the head is formulated as follows, and each sub-weighting function is introduced in the following section.
if $\|X_h - X_{sho}\| \neq 0$,

$$w(X_h) = w(I_1|X_h)w(I_2|X_h)w(I_3|X_h) \quad (1)$$

otherwise,

$$w(X_h) = w(I_1|X_h)w(I_2|X_h)(w(I_3|X_h)+w(I_3|X_h, X_{sho})) \quad (2)$$

,where $\|X_h - X_{sho}\|$ is the Euclidean distance between the joint points of X_h and X_{sho}.

B. Hierarchical Boosting Models

I_1 is the image observation by a horizontal oriented edge detector (see Fig. 2(a)). A variant of boosting algorithm [18] is used to build a three layers cascade classification model [15] $\mathcal{M}$, which outputs the proposal function $w(I_1|X_h)$.

$$w(I_1|X_h) = \{ \begin{array}{ccc} 1 & if & \mathcal{M} \Rightarrow true \\ 0 & otherwise & \end{array} \quad (3)$$

C. Edge Clustering Model

I_2 is the image observation by the Prewitt kernals[9], a contrast enhancement filter and a binary filter (see Fig. 2(b)). The weighting function $w(I_2|X_h)$ is formulated below.

$$w(I_2|X_h) = \{ \begin{array}{ccc} 1 & if & \sum\sum_{(j,k)\in X_h} I_2(j,k) > \alpha \\ 0 & otherwise & \end{array} \quad (4)$$

where $\alpha = \lambda\times$area of X_h ($\lambda = 0.1$, which is determined empirically using training data).

D. Novel Head Top Detector

I_3 is image observation by a vertical oriented edge detector (see in Fig. 2(c)) and a binary filter. $w(I_3|X_h)$ is the confidence weight of the top of the head. Given a potential head region X_h, we evaluate the top of the head region X_t as illustrated in Fig. 2(d) and produce the weighting function below.

$$w(I_3|X_h) = \sum\sum_{(j,k)\in X_t} I_3(j,k) \quad (5)$$

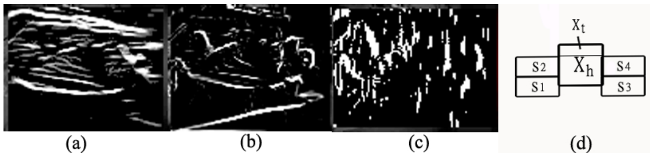

Fig. 2. Image observations for the head: (a) Horizontal oriented edge image I_1 (b)Image by Prewitt kernals and a contrast enhancement filter I_2 (c) Vertical oriented edge image I_3 (d)Definition of potential areas of shoulders S_1, S_2, S_3, S_4, and the top of the head X_t to the head region X_h

E. Obscured Shoulder Detection

There are two distinctive types of shoulder postures: the frontal posture and the side posture. The appearance of the shoulders in frontal postures are detectable by roughly symmetric (obscured) two-side shoulders, but the appearance of the shoulder on side is not conspicuous. Hence, we create a weight function $w(I_3|X_h, X_{sho})$ for potentially heavily obscured frontal shoulders. Instead of contour matching on a number of head-shoulder templates as seen in [8] where shoulder contour is clearly represented, we define four potential regions S_1, S_2, S_3, S_4 of two shoulders as displayed in Fig. 2(d) using vertical oriented edge images as in Fig. 2(c) for I_3. The reason to use four regions instead of two is to accommodate variances of the shoulders' position and heavy obscuration of the shoulders by the cover. In addition, the proposed shoulder detection method largely saves computational time in compared to the contour matching approach [8].

Firstly, we compute the strength of feature exhibiting level c_i for each potential region S_i of the shoulders.

$$c_i = \sum \sum_{(j,k) \in S_i} I_3(j,k) \tag{6}$$

Next, $\{c_1, c_2, c_3, c_4\}$ are compared, and two are selected as the shoulder exhibiting levels (a_1, a_2), which are then used to generate the confidence weight of the shoulders defined by the given head hypothesis X_h according to the symmetrization index of the shoulders Δ and the shoulder exhibiting levels (a_1, a_2).

if $c_1 \geq \beta \wedge c_3 \geq \beta$,

$$(a_1, a_2) = (c_1 - \beta, c_3 - \beta) \tag{7}$$

otherwise if $c_2 \geq \beta \wedge c_4 \geq \beta$,

$$(a_1, a_2) = (c_2 - \beta, c_4 - \beta) \tag{8}$$

otherwise if $\max(c_1, c_2) \geq \beta \wedge \max(c_3, c_4) \geq \beta$,

$$(a_1, a_2) = (\max(c_1, c_2) - \beta, \max(c_3, c_4) - \beta) \tag{9}$$

otherwise,

$$(a_1, a_2) = (-1, -1) \tag{10}$$

, where $\beta = 18$ is determined empirically by training data.

$$\Delta = \|a_1 - a_2\| \tag{11}$$

TABLE I
EXPERIMENTAL RESULTS ON SHOULDER DETECTION

c_1	c_2	c_3	c_4	a_1	a_2	Δ	Importance $w(I_3\|X_h, X_{sho})$
23	29	**37**	10	5	19	14	1.71
10	**35**	**34**	17	16	17	1	33
18	**27**	9	**37**	9	19	10	2.8
17	7	26	27	-1	-1	0	0

*Two figures in (c_1, c_2, c_3, c_4) in **Bold** are selected to generate (a_1, a_2).

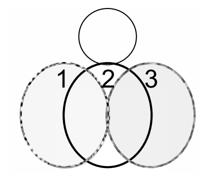

Fig. 3. Head to Torso Candidates: Coarse Classification Type 1, Type 2 and Type 3

The shoulder weighting function $w(I_3|X_h, X_{sho})$ is formulated as follows.

$$w(I_3|X_h, X_{sho}) = \left\{ \begin{array}{ccc} \frac{a_1+a_2}{\Delta} & if & a_1 \geq 0 \wedge a_2 \geq 0 \wedge \Delta > 0 \\ 1 & if & a_1 \geq 0 \wedge a_2 \geq 0 \wedge \Delta = 0 \\ 0 & & otherwise \end{array} \right. \tag{12}$$

The design of the shoulder weighting function is based on (1) the symmetrization of the shoulders and (2) the strength of feature exhibiting level. To illustrate the importance function, where higher confidence weight is given to instances with higher symmetric orientation ($\Delta \downarrow$) and stronger edge exhibiting level($a_1 \uparrow, a_2 \uparrow$), some examples of experimental results are listed in Table I.

Importantly, $w(I_3|X_h, X_{sho}) = 0$ does not necessarily mean that the shoulders are not in the frontal posture because they may be obscured. However, whenever the shoulders exhibit clearly, we utilize the shoulder information I_3 to assist the estimation of the neighboring nodes, i.e. X_h and X_{tor}, and increase the likelihood of the neighboring nodes.

F. Obscured Torso Model

The appearance of the torso varies considerably according to the level of occlusion by the cover, the hands or the arms. Hence, to accommodate large variance on the appearance of the torso, we develop three measurement models to formulate the torso detection model, including an obscured torso measurement model from our previous work [16], [17], a shoulder to torso measurement model and a novel leg joint detection model, which will be introduced in the next section.

The proposed obscured head to torso detector coarsely classify potential torso regions into three categories (Type 1, Type 2 and Type 3) as seen in Fig. 3, and the output of the torso model is the estimated torso type. The algorithm is described as follows.

Obscured Torso Detection Algorithm:

1 if $w(I_3|X_h, X_{sho}) > 0$

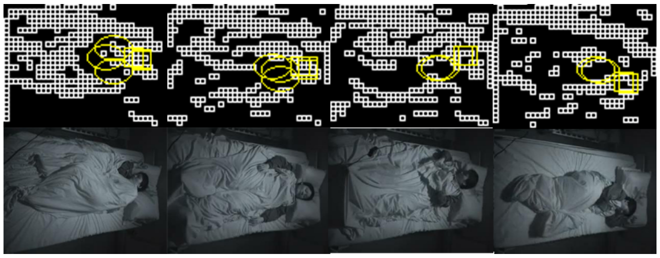

Fig. 4. Edge box maps I_{tor} and raw images: regions with high $w(I_{tor}|X_{tor})$ are highlighted

(clear shoulders exhibit)
1.1 $w(X_{tor}) = w(I_3|X_h, X_{sho})$
1.2 output Type 2.
2 Otherwise
2.1 $X^{'}_{tor} = \arg\max(w(I_{tor}|X_{tor}))$
2.2 if $X^{'}_{tor} \in$ {Type 1, Type 3}
(compute the weight of the leg joint to the torso)
2.2.1 if $w(I_3|X^{'}_{tor}, X_{joint}) < \tau \wedge w(I_3|X^{"}_{tor}, X_{joint}) > \varphi$
(where $X^{"}_{tor}$ =Type 1 if $X^{'}_{tor}$ =Type 3
; otherwise $X^{"}_{tor}$ =Type 3
,and τ, φ are defined in the next section)
2.2.1.1 $w(X_{tor}) = w(I_{tor}|X^{"}_{tor})$
2.2.1.2 output $X^{"}_{tor}$
2.2.2 Otherwise
2.2.2.1 $w(X_{tor}) = w(I_{tor}|X^{'}_{tor})$
2.2.2.2 output $X^{'}_{tor}$

$w(I_{tor}|X_{tor})$ is built from our previous efforts [16] of a covered torso model and an edge box map technique. I_{tor} is the edge box map extracted, and the key concept is to look for a relative flat region as a potential torso candidate and assign higher weight to the area with less number of edge boxes inside.

$$w(I_{tor}|X_{tor}) = (\sum \sum_{(i,j)\in X_{tor}} n(i,j))^{-1} \qquad (13)$$

Due to limited paper length, more details can be found in [16]. Fig. 4 shows some examples of potential torso hypotheses using $w(I_{tor}|X_{tor})$.

G. Obscured Leg Joint Detector

If the estimated torso from the previous section is Type 1 or Type 3, we assume both that the person is lying on his/her side instead of on the back and that the image observation of the leg joint to the torso is detectable. Similar to the design concept of the obscured shoulder detection model, three sub-regions $\{J_{lp}\}_{p=1,2,3}$ are defined to search for the potential leg joint according to the estimated torso type l in order to accommodate variances of the leg joint's position and obscuration of the image features of the leg joint by the cover. Fig. 5 illustrates the image observation I_3 and the sub-regions $\{J_{lp}\}_{p=1,2,3}$ for detecting the leg joint to the torso.

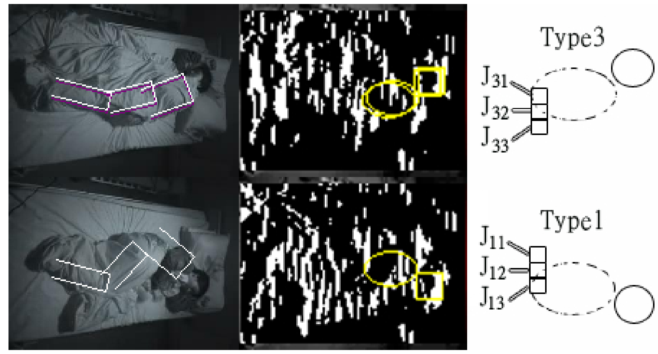

Fig. 5. Final Estimated Pose and Image Observation for Leg Joint Detectors

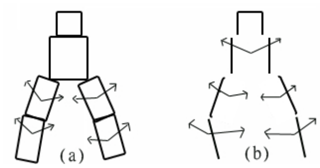

Fig. 6. Stylized Pose Pictorial Structure (a) Template Representation in [10] (b) Template Representation of the Proposed Method

$$w(I_3|X_{tor}, J_{lp}) = w(J_{lp}) = \sum \sum_{(j,k)\in J_{lp}} n(j,k) \qquad (14)$$

if X_{tor} is Type 1,

$$w(I_3|X_{tor}, X_{joint}) = \max(w(J_{11}), w(J_{12}), w(J_{13})) \quad (15)$$

if X_{tor} is Type 3,

$$w(I_3|X_{tor}, X_{joint}) = \max(w(J_{31}), w(J_{32}), w(J_{33})) \quad (16)$$

We assume that $w(I_3|X_{tor}, X_{joint}) \sim \mathcal{N}(m_j, \sigma_j^2)$, and in step 2.2.1 of the previous section, τ and φ are defined as $\tau = m_j - 2 \times \sigma_j$ and $\varphi = m_j$.

IV. Pose Recognition

The proposed pose recognition model is adapted from a lateral walking pose detector by Ramanan et al.[10]. We modify the method to overcome strong edge noise by the cover, to accommodate large variance of features, and to further improve the estimation. We briefly discuss the lateral walking pose model below.

Ramanan et al.[10] introduced a lateral walking pose detector for people tracking. They quantize edge pixels into one of 12 orientations, produce distance transformed edge images [1] for each orientation, compute the chamfer cost separately for each orientation with the manually set rotated edge templates as seen in Fig. 6(a), add the costs together, and select the human configuration with the lowest cost. In addition, they use pictorial structure method [4] for efficient sampling. However, the approach is easily attracted towards strong edge noise generated by the cover and thus tends to produce incorrect pose estimation in our experiments on the covered subjects. Some examples are given in Fig. 7.

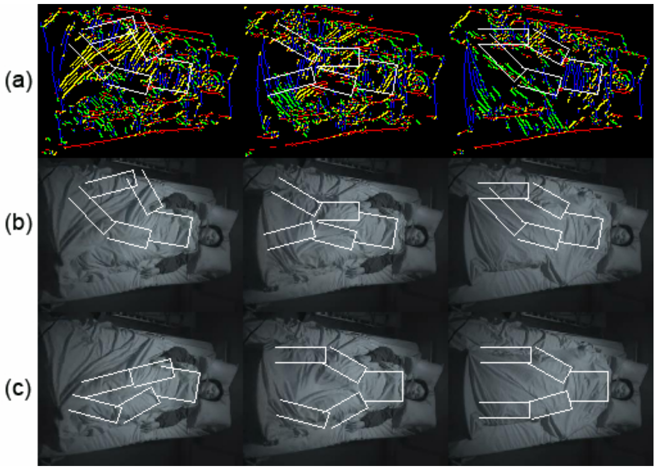

Fig. 7. (a)Separate Edge Orientations with Estimation of [10] (b)Results of [10] (c) Results of the Proposed Method

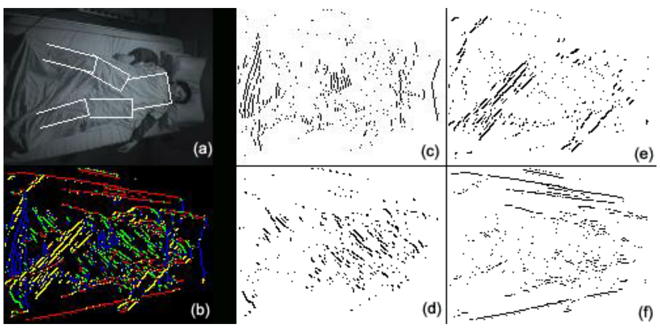

Fig. 8. (a)raw image with the system output (b)combined edge orientation (c) edge orientation vector: (67.5,112.5] and (247.5,292.5], which is used to compute $DT(90)$ (d)edge orientation vector: (112.5,157.5] and (292.5,337.5], which is used to compute $DT(135)$ (e)edge orientation vector: (22.5,67.5] and (202.5,247.5], which is used to compute $DT(45)$ (f)edge orientation vector: (-22.5,22.5] and (157.5,202.5], which is used to compute $DT(0)$

In this work, we improve the model by adding two main modifications. The two major modifications are made on (1) the formula of the matching cost and (2) the representation of the templates as seen in Fig. 6(b).

We quantize edge into eight orientation and extract four vectors of edge orientation information from the input image, which is illustrated in Fig. 8. The four vectors are then processed by distance transformation (DT) and used for chamfer matching pre-trained part-based edge templates generated by twenty manually marked images. Regarding the chamfer cost function, instead of matching on all DT vectors of individual edge orientations and summing up the costs, we select the DT vector(s) of the oriented edges for individual rotated templates. Furthermore, we combine costs from different DT vectors by selecting the minimum of the costs rather than the sum of the costs. For example, if the rotated part template is 20 degree, we define the matching cost of the template as $\min(DT(0), DT(45))$. Moreover, only outside border is used to match for avoiding strong noise generated by the cover as in Fig. 8(b).

TABLE II
POSE ESTIMATION ACCURACY

All Images	Torso	RUL	LUL	RLL	LLL
OUB+cwPose	0.98	0.94	0.95	0.91	0.92
OUB+[10]	0.97	0.68	0.48	0.61	0.35
With Cover	Torso	RUL	LUL	RLL	LLL
OUB+cwPose	0.99	0.94	0.96	0.91	0.94
OUB+[10]	0.99	0.63	0.44	0.55	0.32
No Cover	Torso	RUL	LUL	RLL	LLL
OUB+cwPose	0.96	0.93	0.85	0.89	0.81
OUB+[10]	0.85	0.96	0.70	0.93	0.48

*OUB: proposed obscured upper body model; cwPose: proposed pose recognition method; RUL: right upper leg; LUL: left upper leg; RLL: right lower leg; LLL: left lower leg.

V. EXPERIMENTS

We use two articulated models to represent the human configuration, including two leg human model and one leg human model. The two leg human model has six parts, corresponding to the head, torso and two parts per leg; the one leg human model has four parts, corresponding to the head, torso and two part for the leg. The decision to use which model is based on the cost of chamfer matching on the torso templates. To generate the part templates, we manually marked the location of each part in twenty images.

A. Experimental Setup

A SONY infrared camcorder (DCR-HC-30E) is utilized to capture the data. The infrared video frames were acquired with resolution of 320*240. In order to simulate the environment for diagnosis on sleeping disorders, there was no visible lighting in the filming room and the subject was covered by a sheet. Furthermore, the experimental data was collected with three different occlusion levels (i.e. fully covered, partially covered and without cover) and various body postures.

B. Experimental Results

In evaluation, we tested the model by matching it to 166 images containing a number of unconstrained poses and various occlusion levels (with cover:139; without cover: 27). We also compare the proposed method with [10]. Table II shows the pose estimation accuracy of the proposed algorithms and [10]. If the overlapping area of the estimated body part and the body part is greater than 70%, we count the estimation as an accurate estimation. The pose estimation accuracy in Table II is equal to the number of accurate estimation dividing by the number of estimation.

The experimental results show that [10] obtains lower accuracy for covered subjects and that the proposed methods (OBU+cwPose) outperforms the referenced work overall and for covered subjects. Some matching results are shown in Fig. 9.

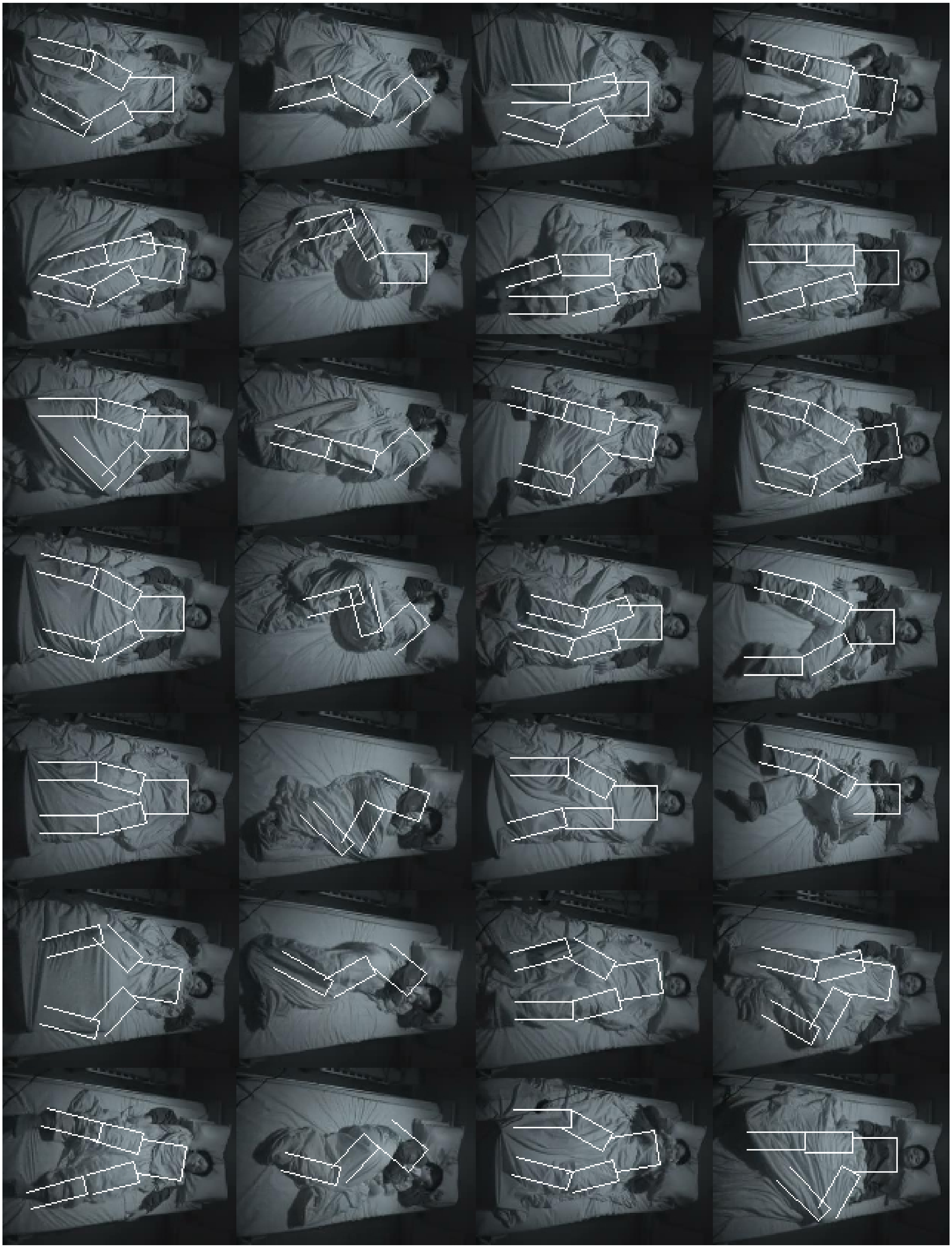

Fig. 9. System Outputs

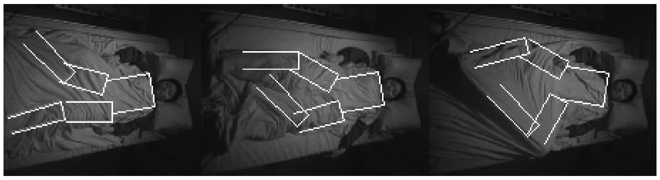

Fig. 10. Results affected by strong edge noises.

C. Limitation and Future Work

Although the sampling technique [4] improves the computational efficiency and works well for un-occluded subjects as in[10], we observe that the estimation of the leg postures suffers both from strong noises by the cover and from weak expression of features, which can be improved by development of the sampling methods in the future work. Some examples are illustrated in Fig. 10. Furthermore, advanced method utilizing partial but fragmented motion information will be investigated to improve the estimation of the body posture.

VI. Conclusion

Analysis of the covered human body from video is a challenging task as traditional computer vision methods such as correlation, template matching, background subtraction, contour models and related techniques for object tracking become ineffective [2], [7] because of the large degree of occlusion for long periods. Difficulties arise from night vision, the shifting of the cover surface with movements, obscuration of the bodies' edges by the cover, and wrinkle noises are compounded by human articulated deformation. In the absence of color, texture and silhouette information in the targeting problem domain, we have presented a novel technique for estimating the pose of a covered human, overcoming the difficulties from poor quality of image cues due to heavy obscuration, from large variance on image features due to unpredictable human behavior to remove or pull back the cover, from poor quality of motion due to heavy obscuration, and from fragmented motion due to partial and occasional movement.

The proposed method contains a novel weak human model to accommodate large variance of image features and a strong pose recognition model adapted from a lateral walking pose detector[10] for people tracking. In evaluation, experimental results show that the proposed model is robust to estimate the pose of a human body with fully or partially covered or without covered. As the number of the experiments in this paper is limited, more experiments will be conducted using patients and volunteers in the Sleep Lab at the Lincoln County Hospital to determine performance on a large scale and to generalize across the variations in human sizes, shapes, and behavior. Furthermore, we will develop a system to diagnose movements characteristic of sleep disturbances.

VII. Acknowledgments

This research is jointly supported by United Lincolnshire Hospitals NHS Trust (ULH collaborative Research Grant) and University of Lincoln for the PhD scholarship of C.-W, Wang. The authors gratefully acknowledge the support of Dr. Neil Gravill and Dr. Simon Matusiewicz for their valuable comments in obstructive sleep apnoea, Dr. Chris Hacking for his generous help in clinical engineering, Dr. Shigang Yue and the reviewers for their comments on the paper.

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