ABSTRACT

Recent advancements in computer vision, particularly by making use of deep learning, have drastically improved human motion analysis in videos. However, these improvements have not yet fully translated into improved performance in clinical in-bed scenarios due to the lack of public datasets representative of this scenario. To address this issue, we introduce BlanketSet, an RGB-IR-D action recognition dataset of sequences performed in a hospital bed. This dataset has the potential to help bridge the improvements attained in general use cases to these clinical scenarios. The dataset is available at rdm.inesctec.pt/dataset/nis-2022-004

Index Terms— Action recognition dataset, RGB-IR-D Video, Motion Capture, Human Pose Estimation, Epilepsy monitoring, Sleep analysis

1 Introduction

Human motion analysis in video has recently seen drastic improvements due to advances in Deep Learning (DL). However, almost all the research in this area was focused on the most general context of people standing up without any occlusions. Furthermore, the difficulties of generalizing DL systems beyond the domains of their training datasets, means these results have not translated to clinical scenarios where the patients being analyzed are lying in beds with blankets occluding them. In order to bridge this domain gap, we provide an opportunity to transfer the improvements attained in more general contexts to these clinical ones by introducing BlanketSet. BlanketSet is a dataset consisting of 405 RGB-IR-D recordings of 14 participants performing 8 different movement sequences in a hospital bed. Each recording was repeated 3 times with different levels of blanket occlusion, so it can be used not just for action recognition, but also for qualitative evaluation of human motion analysis systems. As an example of this second use case, we used BlanketSet to evaluate the pipeline implemented in [1] and found that it improved the performance of a DL human pose estimation system with statistical significance when full-body blanket occlusions were present.

2 Related work

In-bed movement monitoring is done in different contexts, the most relevant ones being epileptic seizure analysis and sleep analysis.

In the area of automatic epileptic seizure classification, there has been significant research, in [2] a system was set up to record RGB-IR-D videos synchronized with EEG data of patients staying at the University of Munich EMU. Then in [3], a collaboration system was implemented to allow clinicians to more easily label the recorded data. IR data acquired with that system was used in [4] to explore DL, particularly transfer learning, in the context of action recognition at EMUs. Data recorded with this system is very promising for future research in this area but is not publicly available, which limits its accessibility in other research contexts.

In the area of sleep analysis, the use of data collected from cameras positioned above the bed has been explored as a less costly and less invasive alternative with promising results [5, 6, 7]. However, the only image dataset of people lying in beds that is publicly available is SLP [8], which contains 14700 RGB and LWIR images, depth maps, and pressure maps of people in static positions as well as 2D position ground truth; it is a fantastic resource but lacks the temporal dimension that is very relevant in contexts with considerable movement such as the analysis of epileptic seizures.

Image and video-based DL systems have been shown to work exceptionally well in tasks related to human motion recognition and classification in general use cases [9, 10, 11], therefore it is reasonable to expect that they would also be able to perform well in the more specific use cases of sleep analysis and epileptic seizure analysis. As with everything related to deep learning, however, large amounts of data are required and, due to the lack of publicly available datasets in these areas, each separate research effort has also had to include the acquisition of its own dataset which significantly hampers the efficiency of the research. The acquisition and publication of datasets such as [12, 13, 14, 15, 16, 17] were instrumental to...
the incredible results attained in the more general use cases. There have also been research efforts into utilizing these broader datasets in epileptic seizure analysis: as previously mentioned, [4] employed transfer learning from the Kinetics-400 [16] and ImageNet [17] datasets to discriminate between two classes of epileptic seizures, and BlanketGen [11] augmented the 3DPW dataset [13] with synthetic blanket occlusions to improve the performance of HybrIK [9] in these scenarios.

3 Methods

3.1 Data Acquisition

The dataset was acquired with an Azure Kinect at the Epilepsy Monitoring Unit (EMU) of the University Hospital Center of São João in several sessions over the course of several months. Covid restrictions changed while the dataset was acquired, this led to the participants wearing masks in some recordings, but not in others. One person participated both before and after the restrictions changed, and therefore both with and without a mask.

To each participant, the data to be recorded was explained, as well as their privacy rights, before they each signed an informed consent form in which they agreed to the recording and publication of their data in the dataset.

3.2 Dataset Design and Parameters

In order to control for as many variables as possible within reason, the different variables of the dataset were split into three categories: controlled variables, semi-controlled variables, and uncontrolled variables.

**Controlled variables** were controlled to cover the dimension space as evenly as possible.

- Movement sequences: 8 movement sequences were performed, which are explained in detail in section 3.3.
- Blanket Initial Position (BIP): There were 3 different initial positions for the blanket: no blanket, fully covering the subject, and pulled down so that only about the feet and lower legs were covered.
- Blanket: Originally 3 different blankets of different thicknesses, colors, and weights (black heavy, white light, and green heavy) were alternated between. In the recordings after the restrictions were lifted, different blankets were used (grey heavy, white light, orange heavy).

**Semi-controlled variables** were randomly sampled from a uniform distribution so as to avoid correlations between them and other variables.

- Lighting: 4 different lighting setups were used: natural lightning controlled by having the window blinds up or down, and having the lights on or off.
- Hand position: Four different hand positions were included: relaxed, fingers spread, fingers stretched touching, and closed fist. Figure 1 displays these hand positions.
- Time between position changes: 30 to 120 beats per minute (BPM) (uniformly sampled with integer precision).

![Fig. 1: The 4 hand positions from left to right: relaxed, fingers spread, fingers stretched touching, and closed fist](image)

Uncontrolled variables were deemed not a priority to control in this dataset, although they could affect the performance of systems trained on the dataset. These variables include the participants’ gender, body shape, clothing, hair color and length, and the time of day.

3.3 Movement Sequences

Each movement sequence consists of switching between a few positions repeatedly, each recording contains 20 position changes. The emphasis was on ensuring that the motions were repeated properly over ensuring they were done perfectly as described, it was deemed more important to have consistency within each set of recordings than within the dataset as a whole. In order to cover all the variations of the controlled variables, each sequence was repeated 9 times, once for every combination of BIP and blanket. The semi-controlled variables were changed with the blanket, such that for every recording with one BIP, there be recordings with the other BIPs and no other changed variables.

After careful consideration, 8 motion sequences were selected, 5 involving the legs and 4 involving the arms (1 involving both the arms and the legs). Each of them was given a code name, as well as a number. They are displayed in figure 2.

1. **Foot to knee**: The participant starts in a resting position facing upwards, they then lift their left foot and place it on top of the right knee, then they reset back to the starting position and repeat the previous steps but with the right foot. This sequence was chosen because it severely displaces the blanket with every repetition, and it includes some self-occlusion (Fig. 2a).
2. **Knee bend**: The participant starts in a resting position facing upwards with their right knee bent and their right foot on the bed next to the left knee, they then switch to the same pose but flipped. This sequence was chosen because, while the overall shape of the legs is not visible under the blanket, the deformation of the blanket contains information about the position of the knee (Fig. 2b).

3. **Swinging legs**: The participant starts in a resting position on the side, with one knee stretched and the other bent at a 90° angle. They then flip which knee is stretched and which is bent. The side on which the participants lie down is randomly decided at the time of recording. This sequence was chosen because the overall shape of the legs can be distinguished under the blankets, and because it has a lot of self-occlusion (Fig. 2c).

4. **Hands to shoulders**: The participant starts in a resting position facing upwards, then they bring their hands up to the opposite shoulders. This sequence was chosen because the amount of interaction between the hands and the blanket varies with each repetition (Fig. 2d).

5. **Belly-down spread**: The participant starts in a resting position facing down, they then spread their arms and legs. This sequence was chosen because it significantly displaces the blanket with each repetition, and because it involves moving both the arms and legs simultaneously without being difficult to coordinate (Fig. 2e).

6. **Torso lean**: The participant starts in a leaning position with the right forearm lying down on the bed and the left arm stretched, they then switch to the same pose but flipped. This sequence was chosen because it includes movement of the torso, which is generally static in the other sequences (Fig. 2f).

7. **Stretched arms**: The participant starts in a resting position facing up with their arms stretched next to them, they then raise their arms up, followed by bringing them down into a T-pose, then bringing them back up before going back to the resting position. This sequence was chosen because it includes a large portion of the range of motion of the shoulders plus it is partially vertical, which is a dimension the other sequences don’t prominently explore (Fig. 2g).

8. **Feet stretched**: The participant starts in a resting position facing up with their feet at 90° to the rest of the leg, they then stretch their feet as far as they can. This sequence was chosen because it consists only of movements of the feet, which are very difficult to notice under blankets (Fig. 2h).

### 3.4 Dataset Utilization for Evaluation of BlanketGen

BlanketSet was used to evaluate the utility of the pipeline implemented in [1] in the task of human pose estimation. Videos from BlanketSet were processed by both the fine-tuned and the pre-trained models. For this, one sequence from each participant was selected, with each movement sequence, as well as each blanket, being present at least once in this selection. The number of videos selected had to be small, so the BIP of the blanket completely off the subject was excluded. BlanketGen had already been evaluated in cases without blanket occlusions in [1] so evaluating in these cases was not a priority for this paper. Figure 3 shows a frame from one of the recordings (a) alongside the same frame with body mesh estimation made by the pre-trained model (b) and one by the fine-tuned one (c).

A survey was conducted and made public where the annotated videos were rated on a scale from 0 to 10, with 0 being a failure to even locate the subject and 10 being perfect annotations. This survey was advertised to all students of the Faculty.
of Engineering of the University of Porto (FEUP) with the dynamic email service provided by the university and it gathered a total of 29 responses.

4 Results

Following the methods described previously, an action recognition dataset was acquired with 8 movement sequences being performed in a hospital bed by 14 participants, with 3 levels of blanket occlusion, various blankets, and at different speeds; it also includes recordings of participants with and without masks.

Videos from BlanketSet were used to qualitatively evaluate the pipeline implemented in [1]. Table 1 describes which recordings were used for the survey as well as the average rating each recording got when annotated with either model, rounded to two decimal cases.

As expected, the determining factor for the quality of the annotations was the blanket initial position (BIP); Table 2 summarizes these results as well as the rating difference between both models and a symmetric 95% confidence interval for these differences calculated with a two-tailed paired t-test.

Table 2: The results separated by BIP. The differences between the results of the two models are listed on the right with a 95% confidence interval.

5 Discussion

The original paper on BlanketGen [1] found that the fine-tuned model performed better than the pre-trained one when there were blanket occlusions but worse when there were not and it posited that this was due to the fine-tuning using a dataset that included fewer videos without blanket occlusions than what the model was pre-trained on.

The qualitative results obtained in this paper corroborate this since the performance improvement was only statistically significant in the videos with full blanket occlusion. They also confirm that the improvement was not due to overfitting, since the fine-tuned model did outperform with statistical significance the pre-trained one in cases with real blanket occlusions.

6 Conclusion

In this paper, we introduce BlanketSet, a dataset that has the potential to aid in the research of human motion analysis in clinical contexts where the patients are lying down in bed, particularly in the cases of epilepsy monitoring and sleep analysis. As an example of a use for BlanketSet, it was utilized to qualitatively evaluate the performance of BlanketGen [1] in the task of human pose estimation.

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8 References

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