Detection of Simulated Clonic Seizures from Depth Camera Recordings

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***Abstract*—Tonic-clonic seizures pose a serious risk of injury to those afflicted. Therefore, patients both in home-based and residential care can require constant monitoring. Technical aids may help by alerting caregivers of detected seizures. So far, the usability of several sensor systems for seizure detection has been shown. However, most of these systems require some sensors to be physically attached to the patient or are limited with respect to their accuracy or robustness. Thus, we investigated the feasibility of using depth image sequences for the detection of seizure-like periodic motion. A static camera setup was utilized to monitor a limited region of interest comparable to a patient's bed during the night. Data of simulated limb motion including seizure-like movement was acquired with help of a robot moving a hand phantom both uncovered and covered by a duvet, ensuring the availability of a known ground truth. Subsequently, a characteristic of the recorded images which may be used to differentiate between normal and seizure-like motion was defined. Finally, linear discriminant analysis was applied to the determined characteristic. We found that the rapid detection of seizure-like periodic motion from depth image sequences is feasible even when the moving limb is covert by a blanket.**

***Index Terms*—vision based seizure detection, periodicity analysis, depth image processing, epilepsy**

I. Introduction

Epilepsy is a chronic disorder affecting about 50 million people around the globe [1]. Additionally, 5 to 25% of patients with brain injuries experience seizures [2]. Particularly patients of the latter group may require continuous monitoring while epileptic patients in home-based or residential care are most vulnerable while alone at night [3], [4]. For these patients, tonic-clonic seizures pose the greatest risk to life as they increase the risk for Sudden Unexplained Death in Epilepsy (SUDEP) especially while the patient is asleep [5], [6].

In either case, technical aids can relieve staff and family of the need for constant manual monitoring by alerting nurses and caregivers of detected seizures. Sensor systems utilized for seizure detection include EEG (electroencephalography), ECG (electrocardiography) PPG (photoplethysmography), EMG (electromyography), systems measuring EDA (electrodermal activity), audio recording systems, accelerometry, magnetometry, and RGB video recording systems [7], [8].

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Most of these systems require some sensors to be physically attached to the patient which may cause discomfort and is impractical for long-term care. Detection systems based on audio recordings are low-cost and may be placed in close vicinity to the patient without physical attachment to the patient. However, these systems show a poor performance with a large number of false alerts [8].

Furthermore, Lende *et al.* [9] recently reaffirmed the need for image based monitoring by evaluating the number of nocturnal seizures identified in a residential setting with help of video monitoring as well as with acoustic detection systems and bed motion sensors. They found that 33% of all seizures and 12% of all clonic seizures observed with help of the video monitoring were neither detected by the bed motion sensors nor the acoustic detection system. In their study, caregivers trained to recognize seizures monitored the video recordings.

Today, a number of approaches exist for seizure detection from RGB video recordings [7], [8], [10]-[12]. Some of these utilize specific clothing [10] or visual markers attached to the patient's extremities which defeats the advantages of a contactless sensor system over systems requiring sensors attached to the patient. Other video recording systems employ seizure detection methods based on motion trajectories [11] or the periodicity of the average luminance in the RGB images [12]. None of these systems allow the patient to be covered during the video recording. A patient sleeping without a blanket is a common occurrence when the patient is a premature infant as is the case for the research of Karayiannis *et al.* [11] and Ntonfo *et al.* [12]. For patients of all other age groups, a solution enabling the vision based detection of clonic seizures despite normal bedding would be preferable.

Additionally, all mentioned RGB-based seizure detection methods except the method developed by Ntonfo *et al.* [12] require elaborate computations. This may be of little relevance for diagnostic applications but appears undesirable when the objective is the rapid detection of an occurring seizure. Ntonfo *et al.* [12] chose an approach based on the detection of periodicity in the recorded movement reflected by the average luminance of the difference between two consecutive images of their RGB video recordings. They found that RGB video recordings of a 10s time window contained sufficient

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information for their algorithm to detect neonatal clonic seizures.

Contrary to RGB camera recordings which scarcely reflect movement away from or towards the camera, a depth camera implicitly records movements in any direction within its field of view. In the following, we show the feasibility of the detection of clonic seizure-like periodic motion of an object both within direct view of a depth camera and covered by a duvet using a periodicity based approach requiring less than 3 s of depth camera recordings.

II. Methods

In order to investigate the feasibility of clonic seizure detection from depth camera data, we recorded a variety of motions including clonic seizure-like periodic movements simulated with help of a robot-mounted hand phantom both within direct view of the utilized depth camera and covered by a duvet. Subsequently, we determined the depth difference present in all pixels of two consecutively recorded depth images and calculated the number of times that the algebraic sign of the depth difference changed for each of the depth difference image pixels within a time window of up to 3s of depth camera recording.

Here, each change of the algebraic sign of the depth difference should indicate a change of direction of the recorded movement. Finally, we applied cross-validated linear discriminant analysis to determine the feasibility of differentiating periodic seizure-like motion from other movements using the number of algebraic sign changes of the depth difference between consecutive depth images recorded over some time window.

A. Data Acquisition

The utilized data was recorded using the depth sensor of a Kinect v2 camera and a hand phantom mounted onto a robotic arm. The Kinect v2 camera has a recording frequency of about 30Hz. The setup as seen from the point of view of the Kinect v2 camera is depicted in Fig. 1 where dark colors indicate a relatively small distance between the camera and the detected surface while lighter colors imply larger distances. Here, the distance between the hand phantom and the Kinect v2 was roughly 1.2m.

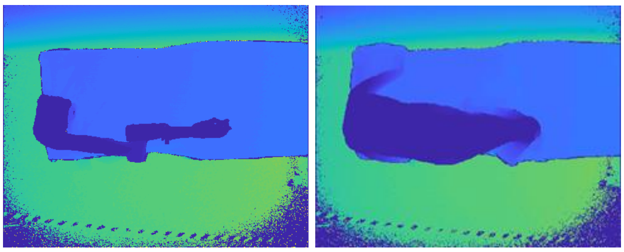

Figure 1. Depth images of hand phantom mounted onto the robotic arm for data acquisition without (left) and with (right) duvet as seen from and recorded by the Kinect v2 camera.

According to Lüders *et al.* [13], the muscle contractions present during clonic seizures occur at a rate between 0.2Hz and 5Hz and in tonic-clonic seizures, the rate of muscle contractions decreases until the contractions disappear. We decided to simulate seizure-like motion with a frequency of up to 3Hz since simulated motions between 1 and 3Hz should be well within the frequency window through which each tonic-clonic seizure should pass.

In order to represent various other types of motion that a patient may exhibit while not experiencing a seizure, the robot motion protocol included a number of movements which may be grouped into the following categories:

- Rest: hand speed of 0 mm/s,
- Random light motion: hand speed of 10 mm/s covering distances of 10 to 15 mm,
- Random strong motion: hand speed of 100 mm/s covering distances of 100 to 300 mm,
- Seizure-like periodic motion: hand speed of 300 mm/s covering distances of 50 to 100 mm.

For the seizure-like periodic motion, the directions of motion were chosen such that the angle between the direction of motion and the depth camera's principal axis varied between 0 and 90 degrees. This setup ensures that the level of seizure detection determined later on is valid irrespective of the observed motion's orientation in space. For random light and strong motions, a new random direction was chosen after a certain distance was traveled. For random strong motion, this distance was chosen randomly from the interval [100, 300] mm while for random light motion, the distance to be traveled was selected at random from the interval [10, 15] mm.

In total, approximately 18000 depth images were recorded: about 3000 depth images of rest, random light and random strong motion were recorded respectively as well as 9000 depth images of seizure-like motion.

B. Pre-Processing

A moving average filter with a window size of ten images was applied to the sequence of depth images in order to smooth out sensor noise present in the recorded data. For clonic seizure detection from sequences of depth images, we are interested in the change of depth in the recordings as observed over time. Therefore, the difference in depth between each pixel of two consecutive images was calculated. In the following, this will be referred to as a depth difference image (DDI). The depth difference of any pixels of a DDI for which the depth difference exceeded 100 mm was reset to 0 mm to exclude depth differences unrealistic for human motion.

Examples of one DDI for each of the four recorded movement categories are shown in Fig. 2 and Fig. 3 for recordings of the hand-phantom with and without blanket covering respectively. Here, dark blue implies no change between the depth of the respective pixel in the consecutive images under consideration while lighter colors indicate greater changes of depth. One may note that only artifacts towards the edge of the field of vision of the depth camera are visible when a motionless scene was observed.

The recording of random light motion leads to the visibility of a thin outline of the moving object while the hand phantom is clearly visible when the robot performs random strong or seizure-like periodic motion. In fact, the DDIs for the latter two cases hardly differ since the speeds of the recorded robot movements of both cases enabled the robot to cover enough distance between the recording times of two consecutive images for the depth difference to be clearly visible in the DDIs.

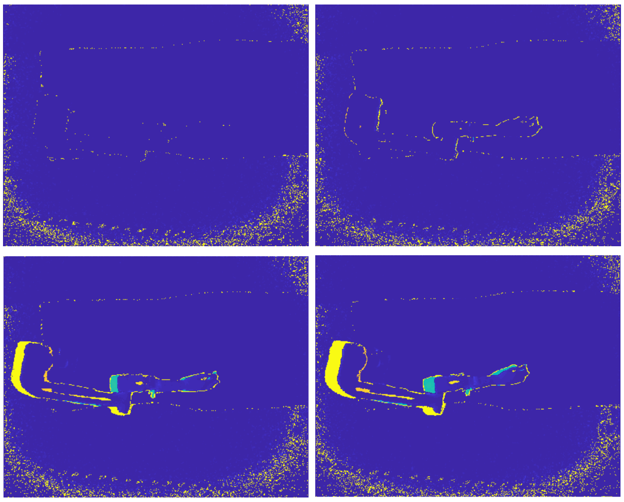

Figure 2. Depth difference image for each of the recorded movement categories, i.e. rest (top left), random light motion (top right), random strong motion (bottom left) and seizure-like motion (bottom right).

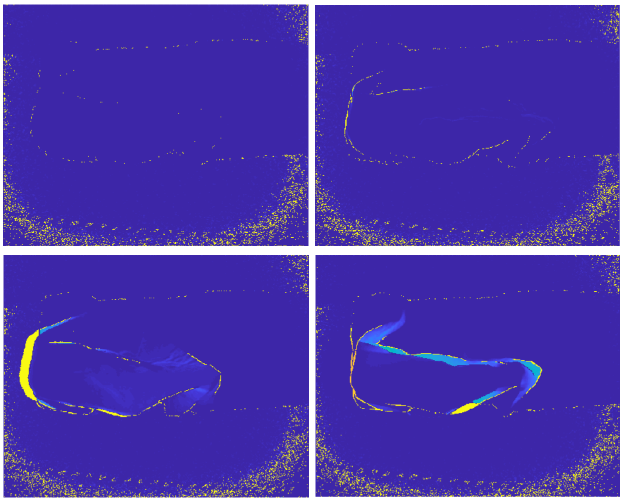

Figure 3. Depth difference image for each of the recorded movement categories, i.e. rest (top left), random light motion (top right), random strong motion (bottom left) and seizure-like motion (bottom right), where the moving hand phantom and robot arm were covered by a duvet.

The depth differences observed when the edges of the moving object conceal or expose parts of the background are most prominently visible in green and yellow since these represent the largest differences in the observed depth at each pixel. Movement towards or away from the depth camera is reflected by a light blue in the DDIs which for the human eye is harder to distinguish from the background than those changes reflected by bright colors.

The use of DDIs renders the background of the considered depth images irrelevant since pixels in which no movement occurred between the current and the previous recorded time instance are set to zero. Consequently, walls, floor, bed frame and mattress do not appear in the DDI just as the floor of the laboratory clearly visible in the depth images in Fig. 1 as well as the table onto which the robotic arm is mounted are not reflected in the DDIs shown in Fig. 2 and Fig. 3. Only the edges of the table may be discernable. Similarly, the decrease in quality of the depth camera recordings towards the edges of the depth images is reflected in the DDIs.

C. *Feature Definition*

Clonic seizures are characterized by repetitive muscle contractions causing motion which periodically changes direction. The number of sign-changes in the difference of observed depths between the pixels of two consecutive images reflects the number of times that the direction of movement changed within a short time window. On the contrary, normal motion of a sleeping person should exhibit much fewer changes of direction within a short time window.

More specifically, the characteristic to be calculated was defined as: f_{sign} = number of sign-changes in the difference of depth between two consecutive images exceeding a threshold d_{sign} (mm) over a number of consecutive images n_{sign}.

For the depth difference threshold d_{sign}, values of 1, 5, 10 and 20 mm were considered while the window sizes n_{sign} that were taken into account covered 30, 45, 60, 75 and 90 consecutive DDIs, i.e. roughly one to three seconds. Therefore, the f_{sign} assigned to each DDI corresponds to the sum of the sign changes observed in all pixels which exceeded the threshold d_{sign} of the current DDI as well as the n_{sign} - 1 preceding DDIs. Therefore, the scale at which the depth of a pixel differed between two consecutive images does not influence the determined characteristic as long as this depth difference does not fall below the depth difference threshold d_{sign} and does not exceed 100 mm, i.e. the color of the depth difference depicted in Fig. 1 and Fig. 2 is only of minor relevance for the calculation of f_{sign}.

The f_{sign} corresponding to the first 89 DDIs of each depth image sequence depicting motion of one of the motion categories were discarded since these cannot be labeled unambiguously. Consequently, 2900 DDIs corresponding to rest, random light and random strong motion respectively as well as 8700 DDIs corresponding to periodic seizure-like motion were used in order to obtain a data set balanced between seizure-like and not seizure-like motion.

D. *Assessment*

In order to evaluate the influence of the depth difference threshold d_{sign} and the number of consecutive images n_{sign} on the applicability of the feature f_{sign} to the detection of clonic seizures, linear discriminant analysis [14] was applied to each combination of d_{sign} and n_{sign} as well as to three different data sets:

- Data acquired without any bedding,
- Data acquired with a duvet covering the hand phantom and the robotic arm,
- And the combination of the first two data sets.

The evaluation of the results for the first two data sets should provide insights into the impact of covering of the moving object on the performance of the proposed seizure detection method. Furthermore, the results of the third data set indicate the usability of the proposed method to the most realistic scenario where motion of relevance may occur both while the patient is covered or uncovered.

All results were obtained utilizing ten-fold cross-validation for model assessment [14]. Here, half of the instances of each fold corresponded to seizure-like motion and the other half to equal parts to each of the other movement categories described in Section 2.1. Each instance consisting of an f_{sign} and the label ("seizure-like" or "not seizure-like") corresponding to the DDI for which it was calculated was assigned to exactly one of the folds.

Several measures designed to reflect the quality of a model exist. However, depending on the application it may be desirable to obtain a model which predicts instances of all considered classes equally well or to have a model which is able to reliably predict all instances of one of the considered classes even if this comes at the cost of a lower rate of correct predictions for measurements corresponding to all other classes. Furthermore, the importance of avoiding incorrect predictions of a class may vary.

In the case of seizure detection, the incorrect prediction of seizures as normal motion could be devastating while the incorrect prediction of normal motion as seizure would be acceptable albeit uncomfortable. Consequently, the model assessment measure for this application should emphasize the correct prediction of seizures whereas the correct prediction of normal motion is of little interest other than that it decreases the number of false alarms.

Then, a measure of interest is the G-Measure defined as the geometric mean of the precision (also known as positive predictive value) and the recall (also known as sensitivity or true positive rate) defined as follows:

$$\text{Precision} = \frac{T_{\text{seizure}}}{T_{\text{seizure}} + F_{\text{seizure}}} \tag{1}$$

$$\text{Recall} = \frac{T_{\text{seizure}}}{T_{\text{seizure}} + F_{\text{noSeizure}}} \tag{2}$$

$$\text{G-Measure} = \sqrt{\text{Precision} \cdot \text{Recall}} \tag{3}$$

here, T_{seizure} describes the number of predictions which correctly label seizure-like motion in the considered DDIs. On the contrary, F_{seizure} denotes the number of instances when a DDI not depicting seizure-like motion was incorrectly classified as showing seizure-like motion while $F_{\text{noSeizure}}$ provides the number of predictions which incorrectly labeled seizure-like motion as normal motion.

The prediction results obtained for linear discriminant analysis utilizing each pair of d_{sign} and n_{sign} under consideration are presented in terms of the achieved number of correct and incorrect predictions for each class label as well as the precision, recall and G-Measure.

III. Results

In order to obtain insights into the feasibility of using the proposed method for the detection of seizure-like periodic motion in different application scenarios, three distinct data sets were evaluated. All results are provided in terms of the cross-validated precision, recall and G-Measure as well as their standard errors and the number of correct and incorrect predictions over all cross-validation folds found by applying linear discriminant analysis to the feature f_{sign} for various combinations of d_{sign} and n_{sign}.

TABLE I. Results for Data Recorded Using a Hand Phantom to Simulate Motion Found by Applying Cross-validated Linear Discriminant Analysis to the Feature f_{sign} for Each Combination of Depth Difference Threshold d_{sign} and Number of Considered DDIs n_{sign}. For Each Class Label (Seizure-Like Periodic Motion and Not Seizure-Like Motion), 8700 DDIs Were Considered.

d_{sign}	n_{sign}	Correct predictions		Incorrect predictions		Precision	Recall	G-Measure
		seizure-like	not seizure-like	seizure-like	not seizure-like			
1 mm	30	8700	7220	1840	0	0.87±0.036	1±0	0.93±0.019
1 mm	45	8700	7335	1365	0	0.88±0.036	1±0	0.94±0.019
1 mm	60	8700	7542	1158	0	0.89±0.035	1±0	0.94±0.018
1 mm	75	8700	7950	750	0	0.93±0.028	1±0	0.96±0.015
1 mm	90	8540	8595	105	160	0.99±0.011	0.98±0.012	0.99±0.0077
5 mm	30	8700	7045	1655	0	0.85±0.031	1±0	0.92±0.017
5 mm	45	8700	6674	2026	0	0.82±0.032	1±0	0.90±0.017
5 mm	60	8700	6561	2139	0	0.81±0.030	1±0	0.90±0.016
5 mm	75	8700	6652	2048	0	0.82±0.030	1±0	0.90±0.016
5 mm	90	8700	6412	2288	0	0.80±0.022	1±0	0.89±0.012
10 mm	30	8700	7133	1567	0	0.86±0.031	1±0	0.92±0.017
10 mm	45	8700	6875	1825	0	0.83±0.027	1±0	0.91±0.015
10 mm	60	8700	6866	1834	0	0.84±0.030	1±0	0.91±0.016

10 mm	75	8700	6585	2115	0	0.81±0.026	1±0	0.90±0.014
10 mm	90	8700	6351	2349	0	0.79±0.025	1±0	0.89±0.014
20 mm	30	8700	7008	1692	0	0.85±0.030	1±0	0.92±0.016
20 mm	45	8700	6866	1834	0	0.83±0.029	1±0	0.91±0.016
20 mm	60	8700	6958	1742	0	0.84±0.032	1±0	0.92±0.017
20 mm	75	8700	6844	1856	0	0.83±0.029	1±0	0.91±0.016
20 mm	90	8700	6331	2369	0	0.79±0.024	1±0	0.89±0.015

TABLE II. RESULTS FOR DATA RECORDED USING A HAND-PHANTOM COVERED BY A DUVET TO SIMULATE MOTION FOUND BY APPLYING CROSS-VALIDATED LINEAR DISCRIMINANT ANALYSIS TO THE FEATURE f_{sign} FOR EACH COMBINATION OF DEPTH DIFFERENCE THRESHOLD d_{sign} AND NUMBER OF CONSIDERED DDIS n_{sign}. FOR EACH CLASS LABEL (SEIZURE-LIKE PERIODIC MOTION AND NOT SEIZURE-LIKE MOTION), 8700 DDIS WERE CONSIDERED.

d_{sign}	n_{sign}	Correct predictions		Incorrect predictions		Precision	Recall	G-Measure
		seizure-like	not seizure-like	seizure-like	not seizure-like			
1 mm	30	8539	7160	1540	161	0.86±0.037	0.98±0.0083	0.92±0.021
1 mm	45	8700	7301	1399	0	0.87±0.036	1±0	0.93±0.019
1 mm	60	8700	7471	1229	0	0.89±0.035	1±0	0.94±0.019
1 mm	75	8700	7680	1020	0	0.91±0.035	1±0	0.95±0.019
1 mm	90	8540	7849	851	0	0.92±0.033	1±0	0.96±0.018
5 mm	30	8700	7053	1647	0	0.85±0.029	1±0	0.92±0.016
5 mm	45	8700	6819	1881	0	0.83±0.029	1±0	0.91±0.016
5 mm	60	8700	6500	2200	0	0.81±0.029	1±0	0.90±0.016
5 mm	75	8700	6151	2549	0	0.77±0.011	1±0	0.88±0.0062
5 mm	90	8700	6473	2227	0	0.80±0.020	1±0	0.89±0.011
10 mm	30	8700	6812	1888	0	0.83±0.027	1±0	0.91±0.015
10 mm	45	8700	6995	1705	0	0.85±0.030	1±0	0.92±0.016
10 mm	60	8700	7037	1663	0	0.85±0.035	1±0	0.92±0.019
10 mm	75	8700	7413	1287	0	0.88±0.036	1±0	0.94±0.019
10 mm	90	8700	7456	1244	0	0.88±0.031	1±0	0.94±0.016
20 mm	30	8700	6643	2057	0	0.82±0.028	1±0	0.90±0.015
20 mm	45	8700	6804	1896	0	0.83±0.032	1±0	0.91±0.017
20 mm	60	8700	7003	1697	0	0.85±0.034	1±0	0.92±0.019
20 mm	75	8700	7330	1370	0	0.88±0.036	1±0	0.93±0.019
20 mm	90	8700	7219	1481	0	0.86±0.032	1±0	0.93±0.017

TABLE III. RESULTS FOR DATA RECORDED USING A HAND-PHANTOM WITH AND WITHOUT DUVET COVERING TO SIMULATE MOTION FOUND BY APPLYING CROSS-VALIDATED LINEAR DISCRIMINANT ANALYSIS TO THE FEATURE f_{sign} FOR EACH COMBINATION OF DEPTH DIFFERENCE THRESHOLD d_{sign} AND NUMBER OF CONSIDERED DDIS n_{sign}. FOR EACH CLASS LABEL (SEIZURE-LIKE PERIODIC MOTION AND NOT SEIZURE-LIKE MOTION), 8700 DDIS WERE CONSIDERED, I.E. 17400 DDIS IN TOTAL.

d_{sign}	n_{sign}	Correct predictions		Incorrect predictions		Precision	Recall	G-Measure
		seizure-like	not seizure-like	seizure-like	not seizure-like			
1 mm	30	14457	12017	5383	2943	0.74±0.020	0.83±0.018	0.78±0.0086
1 mm	45	14574	12034	5366	2826	0.74±0.020	0.84±0.012	0.78±0.0093
1 mm	60	14605	12325	5075	2795	0.75±0.015	0.84±0.020	0.79±0.0037
1 mm	75	15071	12571	4829	2329	0.76±0.015	0.87±0.0044	0.81±0.0070
1 mm	90	14305	12441	4959	3095	0.75±0.013	0.82±0.022	0.78±0.010
5 mm – 20 mm	30 – 90	17400	14500	2900	0	0.86±0.0019	1±0	0.93±0.0010

The results found for the data set acquired using an uncovered robotic arm and hand phantom are given in Table I. Here, the highest G-Measure of 0.99 was obtained for a depth difference threshold of d_{sign} = 1 mm and a window size of n_{sign} = 90. Simultaneously, this was the only setting for which some DDIs corresponding to recordings of seizure-like periodic motion were not detected.

Similarly, the results obtained for the data set featuring recordings of the robotic arm and hand phantom both covered by a duvet are provided in Table II. Again the highest G-Measure was found for a depth difference threshold of d_{sign} = 1 mm and a window size of n_{sign} = 90. Here, none of the DDIs corresponding to recordings of seizure-like periodic motion were classified incorrectly. Generally, linear discriminant analysis correctly classified all DDIs corresponding to recordings of seizure-like periodic motion for 19 of the 20 combinations of the depth difference threshold d_{sign} and the window size n_{sign} when only recordings of motion with or without covering were utilized.

Additionally, these first two data sets were combined into a joint third data set. The results for this third data set are shown in Table III. Contrary to the best results of the first two data sets, the highest G-Measure for the joint data set was found for any depth difference threshold of $d_{\text{sign}} \geq 5$ mm combined with any of the considered window sizes.

Considering only results obtained for $d_{\text{sign}} \geq 5$ mm, the results for data obtained without covering given in Table I suggest that the number of incorrectly classified normal motion instances increases for longer time frames while the results for data obtained with a duvet covering the hand phantom and robotic arm shown in Table II indicate the opposite for $d_{\text{sign}} \geq 10$ mm.

IV. Discussion

The DDIs corresponding to periodic seizure-like motion are identified correctly in almost all cases except for f_{sign} determined using the smallest considered depth difference threshold d_{sign} = 1 mm. Thus, f_{sign} for $d_{\text{sign}} \geq 5$ mm combined with any of the considered window sizes n_{sign} reliably reflects the presence of periodicity in seizure-like motion even when the moving object is covered by a blanket as a seizing patient lying in bed.

While the reliable detection of seizure-like motion is the main objective, another goal is to minimize the number of false alerts, i.e. recordings of normal motion mistakenly classified as seizure-like motion. Although the best results overall were obtained for a depth difference threshold of d_{sign} = 1 mm and larger window sizes n_{sign} for the cases where both data sets were treated individually, the depth difference threshold d_{sign} = 1 mm should be regarded with caution since the results for the combination of both data sets imply that such a small depth difference threshold causes a lack of robustness with respect to variations in the recording setting including variations in the proportions of the moving object.

In the context of seizure detection, a short response time is desirable as one would like a seizure detection system to reliably raise an alarm as soon as possible after the onset of a seizure. Therefore, we propose the use of n_{sign} = 30 and d_{sign} = 5 mm, leading to a G-Measure of 0.92 for both data sets when each is considered individually and a G-Measure of 0.93 when both training and test data include DDIs corresponding to recordings of covered as well as uncovered moving objects. For these parameters, approximately 1 s of depth image recordings is required for the detection of seizure-like motion.

V. Conclusion

We found that the detection of seizure-like motion from recordings of depth image sequences is feasible. Furthermore, the calculation of only one characteristic of the recorded images, namely the number of sign-changes of the depth differences between all pixels of consecutive depth images counted over some time window, is sufficient to differentiate seizure-like motion from other motions and rest even when the moving object is covered by a duvet. The information contained in depth camera recordings over a time window of approximately 1 s was found to suffice for the task at hand.

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