Graduate thesis

NTNU
Norwegian University of Science and Technology
Faculty of Medicine and Health Sciences
Department of Circulation and Medical Imaging

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Visualisation of limb movements by accelerometers in sedated patients

Graduate thesis in Programme of Professional Study, Medicine
Supervisor: Nils Kristian Skjærvold
May 2021

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ABSTRACT

Background

The prognostication of neurological outcome in sedated ICU patients is challenging. Multiple clinical scoring schemes and examinations are used, where different motoric responses are important input variables. Accelerometric sensors provide an opportunity to precisely and objectively measure abnormal limb movements but is currently not exploited within this field of medicine. We therefore aimed at using accelerometric sensors in a controlled postoperative setting to examine how these data behave in patients going from deeply anaesthetized to fully alert. These data will consist of 12 continuous variables from each patient (3 axes from 4 limbs), which is not easy to interpret in a clinical setting. A second aim of the study was therefore to develop a method for threshold detection and visualization that can possibly be incorporated into an electronic health record.

Methods

We included 10 postoperative heart surgery patients. While observed by a study operator, accelerometric data were collected from all four extremities while the patients were awakening from general anaesthesia. The data from each patient were imported into a time-series data-matrix and for each extremity combined into one acceleration vector. We manually tuned a threshold detection algorithm based on the first undisturbed period of the time-series data in coherence with the visually observed patient movements. Finally, the acceleration peaks were summed within 1-minute epochs to visualize the movement data as heatmaps.

Results

In all patients, the accelerometers detected changes in limb movements in accordance with observations by the study operator. The analyses provided heatmaps that visualize the period in which each patient regained consciousness.

Conclusion

In this study we show that accelerometers can be used to simultaneously detect movement in all four limbs of intensive care patients as they are awakening from anaesthesia. We propose a novel data processing and visualization method where the complex data are condensed into a two-dimensional (time/movement) heat map from each limb, clearly visualizing the amount of movements in 1-minute epochs.

INTRODUCTION

Critically ill patients exposed to dangerous disturbances to their central nerve system may develop neurological impairments that cause unconsciousness or severe disabilities(1). Poor neurological outcome is hard to recognize as long as the patient is sedated and will often be revealed only substantially long after its withdrawal. The issue poses significant stress to the next of kin and healthcare providers, and at a high cost for health institutions. Therefore, there is a need for methods to better monitor and predict the individual cognitive outcome of critical care treatment.

As non-standardized neurological examination is inaccurate to prognosticate neurologic outcome (2), the American Academy of Neurology guidelines recommend that clinicians use standardized assessment scales for clinical examination (3). The Coma Recovery Scale Revised (CRS-R) guides clinicians in assessment of auditory, visual, motor, verbal, communicative and arousal functions and is recommended by the American Congress of Rehabilitation Medicine for its diagnostic validity and reliability(4). The Glasgow Coma Scale (GCS) is a shorter, yet similar scale widely applied in acute assessment of consciousness, e.g. after trauma.

In addition to clinical examination, a series of supplementary methods are essential. EEG has a central role in the assessment of brain function, and some causes and complications of coma can only be diagnosed with the aid of EEG. EEG requires expert interpretation, and lack of interoperator reproducibility is still a challenge (5,6). Continuous EEG is emerging as a

method of functional brain monitoring and might be a solution that offers notable advantages compared to serial EEG recordings. However, with the current lack of automated signal processing methods, the work load of such a recording is an overwhelming challenge(5). Examination of somatosensory evoked potentials and auditory evoked brainstem responses are valuable, although less available, complements to EEG (7,8). Repetitive CT scans are useful to locate severe morphologic changes. MRI (Magnetic Resonance Imaging) is a complex and difficult examination in the subacute period, although it is an excellent tool in the follow-up of patients (9,10,11). There are a few available blood tests among which neuron-specific enolase is used to predict poor outcome especially after cardiac arrest (12, 13). Finally, some studies are suggesting that cerebral oximetry with near-infrared spectroscopy can predict ICU delirium and mortality (14,15). There is a need for a supplementary continuous monitoring technology which is ready to be implemented at bed-side posts.

Motoric responses, both quantitative (the very presence of limb movement) as well as qualitative (the type of movements, like shivering, seizures, myoclonus, etc.), are essential in all neurologic examination scores and the overall clinical evaluation for coma recovery. However, it is often hard to tell whether a patient has moved her limbs during a given period or not, or to classify the exact type of movement from clinical observation only. It is therefore likely that the use of accelerometric sensors can detect limb movements precisely and objectively, thus improving the overall quality of movements recording.

Accelerometry is a well know technology that has been widely applied in different fields of research and in everyday electronic products. In medical research, accelerometers are used in longitudinal epidemiological studies of physical activity and health. Accelerometers have also been used in critical care studies on the topic of physical activity, sleep and agitation monitoring (16,17). From this research we know that accelerometric data correlates well with observed movements(18).

To the best of our knowledge, including a systematic review from 2015 (19), there are no published articles on motion registration in connection to neurologic outcome prognostication. Thus, we believe abnormal muscular movements in brain-injured patients is an understudied field of critical care medicine and could possibly provide a new tool for

function recovery prediction. The rather chaotic looking 3-dimensional raw-data from accelerometers mandates some processing in order to provide information to the health personnel. We therefore chose to start our studies into this new field by examining the awakening from sedation in post cardiac surgery patients due to the very controlled environment where we can precisely detect the transformation from medically induced unconsciousness to fully awake over a short period of time. In this novel work we take a first look at how accelerometers can detect limb movements, focusing only on the amount of movement in each limb as a function of time. We further propose a method for visualization where we make the information accessible to health care providers with understandable graphics that can be incorporated into an existing electronic health record.

MATERIAL AND METHODS

Study population, ethics and confidentiality

The study was conducted at Trondheim University Hospital, at the thoracic intensive care unit. Following ethical approval and signed consent, ten patients admitted for elective heart surgery were included, who went through either a coronary artery bypass grafting or valve replacement surgery. Notably, these patients are supervised after the operation in medically induced coma, until certain parameters meet acceptable levels and the sleep-inducing medicament is deprescribed. The patients arrive at the hospital awake, therefore able to give consent as a participant of the study and they constitute a homogenous group with relatively low complexity. In addition, the thoracic intensive unit where the participants were supervised served as a controlled environment, well suited for data measurements in a pilot study of this kind.

Equipment and data handling

Four wireless 3D accelerometric sensors of the type AX3 (Axivity Ltd, Newcastle, UK) were used to sample and store movement information. The accelerometer detects movement, vibrations and orientation changes in all 3-axis (x, y, z) at high precision. The sensors in this study were configured in a custom software to collect data at a frequency of 100 Hz with a range set to 4 gravitational units (g). The device incorporates a real time quartz clock and

Flash based on-board memory that stores data as CWA-files. We verified that simultaneously used sensors were time-synchronized by inducing a sharp shake to them all at the beginning and end of each experiment. Data were exported as CSV-files and analysed with the Python programming language (20).

Study protocol

To collect accelerometric data from the participants, accelerometers were attached to wrists and ankles. The accelerometers were placed post-operatively after arriving at the ICU, five to ten minutes prior to deprescription of anaesthetics. The observation lasted until the extubation, which occurred at the point where the care providers found the patient awake enough to breathe without respiratory help. The study observer remained in the patient's room, unobtrusive, during the observation period and noted the presence of movement on all limbs.

Analyses

The 3D accelerometric data from all four extremities in each patient were imported into a time-series data-matrix. First, the three-dimensional acceleration vector for each extremity was combined into one acceleration vector according to

$$A = \sqrt{x^2 + y^2 + z^2} - 1.$$

Secondly, a peak finder from the package *SciPy* was applied with height $50\sigma + \mu$, where σ was the standard deviation and μ the mean of the first stabilizing period when the patient was fully immobile, usually set to 2 minutes. The value 50 was found by manual tuning. The time-distance of the function was set to 50. The usage of the peak finder enabled the identification of a number of defined movements and their acceleration value. Finally, the acceleration peaks were summed within 1-minute epochs to visualize the movement data as heatmaps. Thus, the three-dimensional dataset obtained with a frequency of 100 Hz was reduced to a one-dimensional set which indicates movement within every minute. This greatly reduces the amount of data that the clinician encounters and eases the interpretation. In the

final analysis, all data were truncated to ten minutes starting two to three minutes before the first detectable movement.

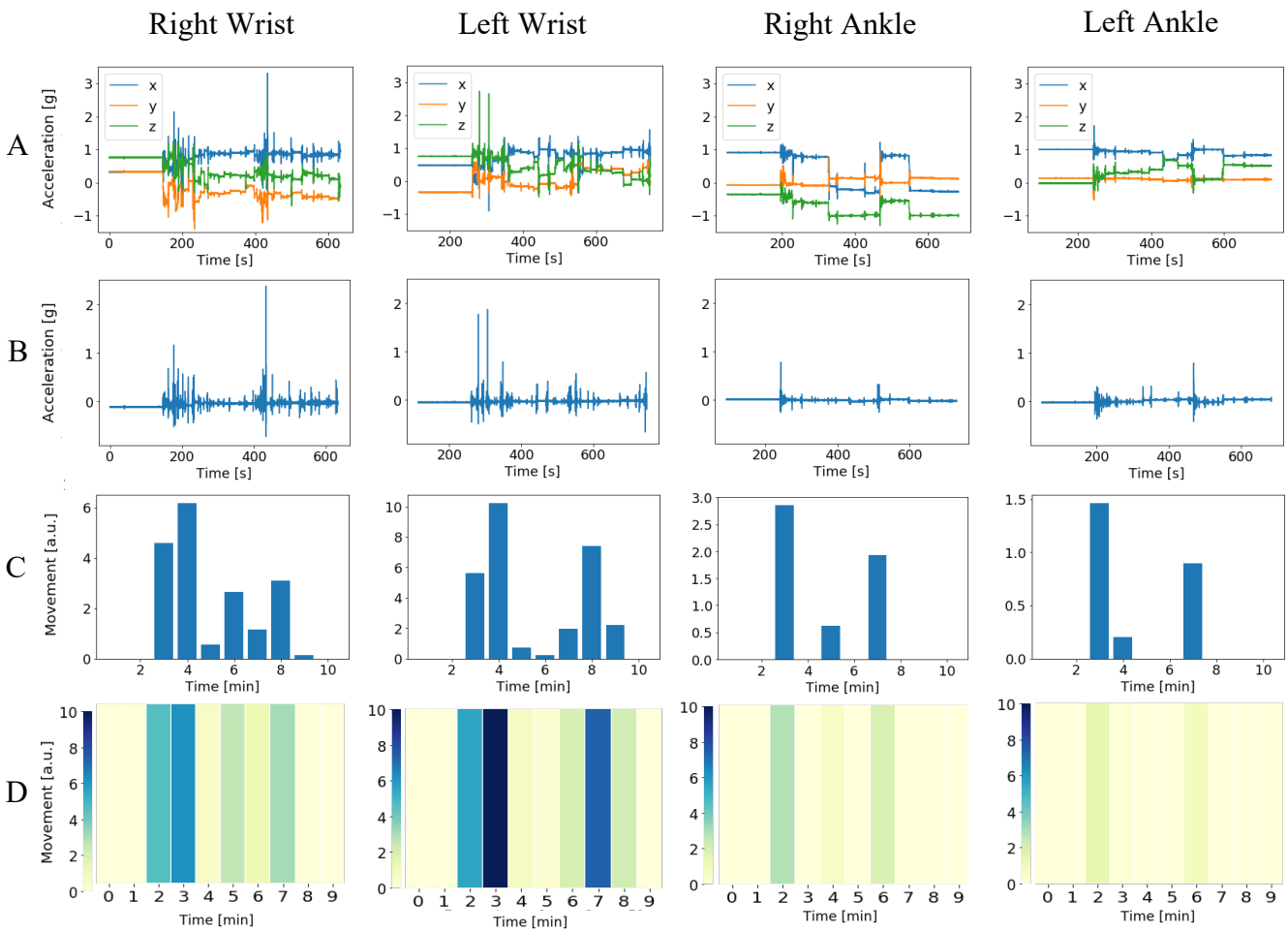

Fig 1: Example of the stages of data and graphical processing from one study subject, one column for each of the four limbs and the rows according to: A) Raw accelerometric data in three dimensions, B) 3D data condensed to one variable per limb, C) total amount of limb movement shown as histograms in 1-minute epochs, D) heat-plot of the data from C).

RESULTS AND DISCUSSION

In all patients, the accelerometers detected a change from no limb movements before deprescription of sedation to various degrees of movement in one or several limbs upon awakening. The method worked well both to detect and to visualize the quantitative amount of movement in each patient and limb as a function of time, as shown in Fig. 2. Note that the accelerometric value scales displayed by depth of color are relative for each dataset and varies by more than tenfold. This is in accordance with our observations, where we saw that the amount of limb-movements was highly individual. In the future, a system for automatic visualization of limb movements must have some predefined automated methods to autotune the scales.

The time from de-prescription of sedation until awakening varied substantially. Therefore, the start of the ten-minute time sequences depicted in Fig. 2 were chosen individually for each dataset to visualize the period in which each patient regained consciousness. As a consequence, the heatmaps do not show time passed since deprescription of sleep-inducing medicine.

We observed that most subjects tend to abruptly move two to four extremities upon awakening, before calming down. The overall visual impression of Fig 2 is therefore in accordance with our clinical impression. Subject b) and f) displayed mostly wrist movement to begin with, while subject i) clearly displayed

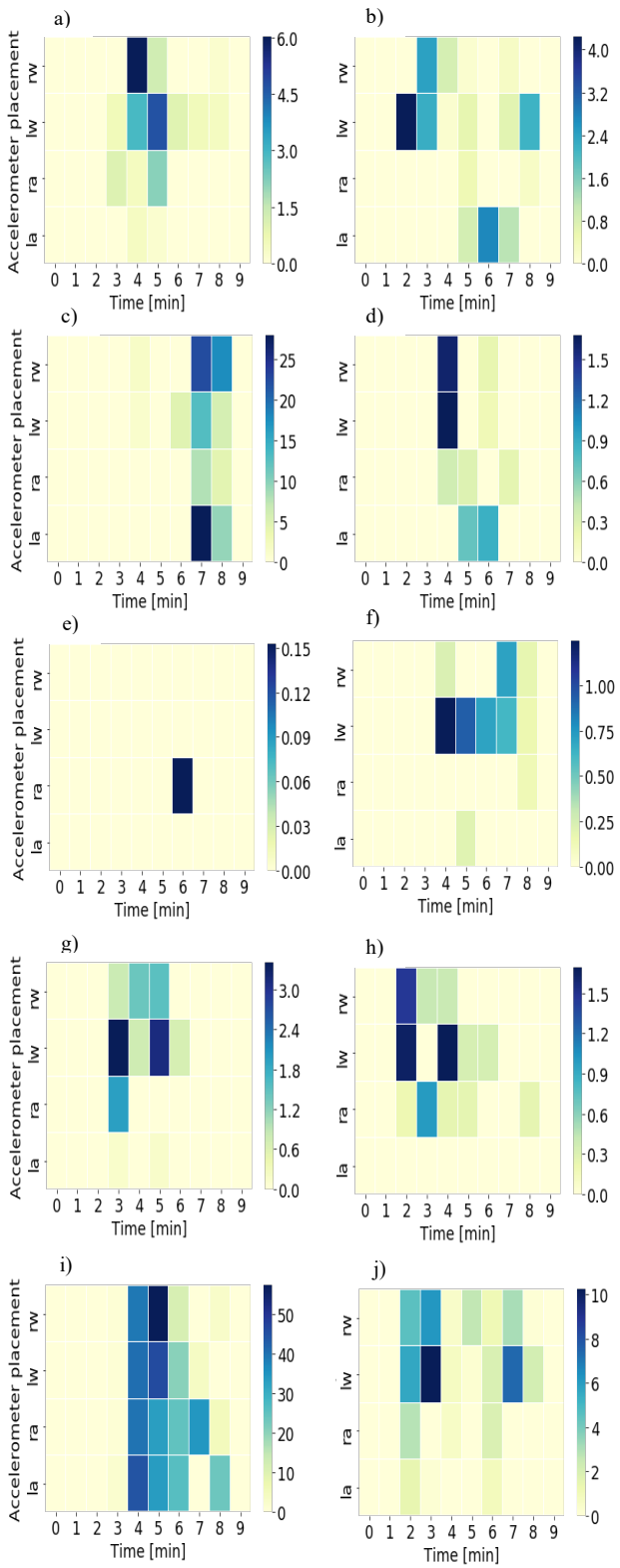

Fig 2: Heat map of limb movements in all 10 patients (a) to j)) with amount of movement for each limb as a function of 1-minute time epochs over 10 minutes. (la: left ankle, ra: right ankle, lw: left wrist, rw: right wrist)

movement in all four extremities upon awakening. Subject e) stands out with almost no movement, perhaps explained by Parkinson Disease, as this particular subject suffered from this diagnosis. From the heatmaps obtained from the accelerometers, a clinician could accurately determine when the patient had awoken for all patients.

Fig 2: Heat map of limb movements in all 10 patients (a) to j)) with amount of movement for each limb as a function of 1-minute time epochs over 10 minutes. (la: left ankle, ra: right ankle, lw: left wrist, rw: right wrist)

Clinical observation and characterisation of limb movements in unconscious patients in the intensive care unit is an important but challenging task. In this study, we show that it is possible to detect and visualize *the amount* of movements. There are several known types of abnormal movements depending on the etiology of the underlying brain injury, e.g. anoxic, inflammatory and traumatic (21). Especially, early myoclonus has long been known to predict poor outcome after cardiac arrest (22). In this first study, and with this study population, we did not aim at doing any qualitative movement characterisation. We do believe this should be possible with the use of accelerometers, which this study supports. It will, however, require more complex data processing algorithms made from larger, classified datasets including both accelerometric data and clinically validated brain injury diagnosis.

Accelerometers are not currently established medical devices in clinical settings, albeit this research show that there are indeed possibilities. We therefore believe accelerometers are low-cost non-invasive equipment that warrant further research to find suitable fields of use.

A limitation to this trial is as with all pilot trials the low number of participants. Another limitation is that we chose to study uncomplicated post-surgery patients and not the designated user population of critically ill patients with a potential brain injury. The reason for this is stated in the manuscript.

CONCLUSION

In this pilot study we show that accelerometers can be used to simultaneously detect movement in all four limbs of intensive care patients. We propose a novel data processing and visualization method where the complex data are condensed to a two-dimensional (time/movement) heat map from each limb, clearly visualizing the amount of movements in 1-minute epochs. The movements visualized in the map were in accordance with our visual observations.

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First of all, I would like to thank my supervisor Nils Kristian Skjærvold for excellent guidanc. I also want to thank Sigrid S. Fuglerud at department of Electronic Systems at NTNU for inventing the Pyhtonscript required to do the analysis. In addition, everyone at HUM Research Group deserves recognition for supporting me throughout the process. Finally, I would like to thank the patients who volunteered to be subjects in this pilot study.

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APPENDIX

Pythonscript

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import math
from datetime import datetime
from scipy import signal
from scipy.signal import find_peaks

def import_file(filename, start, stop):
    df=pd.read_csv(filename)[start:stop]
    new_labels=["time","x","y","z"]
    df.columns=new_labels
    df.time=pd.to_datetime(df.time)
    df.set_index("time", inplace=True)
    #df["date"]=df.index
    df["abs"]=np.sqrt(df.x.pow(2)+df.y.pow(2)+df.z.pow(2)) -1
    return df


def part(df,L,tsec,minutes,height_str):
    freq=math.ceil(len(df.index)/tsec)
    base_mean=df['abs'][0:minutes*60*freq].mean()
    base_std=df['abs'][0:minutes*60*freq].std()
    parted_df=np.zeros((L*freq,int(tsec/L)))
    peaks_df_sum=np.zeros(int(tsec/L))
    peaks_df_amp=np.zeros(int(tsec/L)) #peak amplitude, show how much
acceleration

    print(base_std)
    print(base_mean)
    for i in range(int(tsec/L)-1):
        parted_df[:,i]=df['abs'][i*L*freq:i*L*freq+L*freq]
        peaks_temp, _ = find_peaks(parted_df[:,i],
height=height_str*base_std+base_mean,distance=50)
        peaks_temp2, _ = find_peaks(-parted_df[:,i],
height=height_str*base_std-base_mean,distance=50)
        peaks_df_amp[i]=parted_df[peaks_temp,i].sum()-
parted_df[peaks_temp2,i].sum()
        peaks_df_sum[i]=len(peaks_temp)
    return [parted_df,peaks_df_amp, peaks_df_sum]


def trunc(rw,lw,ra,la):
    rw['date'] = rw.index
    lw['date'] = lw.index
    ra['date'] = ra.index
    la['date'] = la.index
```

```
    if (rw.date[1] >= lw.date[1]) and (rw.date[1] >= ra.date[1]) and
(rw.date[1] >= la.date[1]):
       s1 = rw.date[1]
    elif (lw.date[1] >= rw.date[1]) and (lw.date[1] >= ra.date[1])and
(lw.date[1] >= la.date[1]):
       s1 = lw.date[1]
    elif (ra.date[1] >= rw.date[1]) and (ra.date[1] >= lw.date[1])and
(ra.date[1] >= la.date[1]):
       s1 = lw.date[1]
    else:
       s1 = la.date[1]

    if (rw.date[-1] <= lw.date[-1]) and (rw.date[-1] <= ra.date[-1])
and (rw.date[-1] <= la.date[-1]):
       s2 = rw.date[-1]
    elif (lw.date[-1] <= rw.date[-1]) and (lw.date[-1] <= ra.date[-
1])and (lw.date[-1] <= la.date[-1]):
       s2 = lw.date[-1]
    elif (ra.date[-1] <= rw.date[-1]) and (ra.date[-1] <= lw.date[-
1])and (ra.date[-1] <= la.date[-1]):
       s2 = lw.date[-1]
    else:
       s2 = la.date[-1]

    rw_t=rw.truncate(before=s1, after=s2, axis=None, copy=True)
    lw_t=lw.truncate(before=s1, after=s2, axis=None, copy=True)
    ra_t=ra.truncate(before=s1, after=s2, axis=None, copy=True)
    la_t=la.truncate(before=s1, after=s2, axis=None, copy=True)
    rw['time'] = (rw['date']-rw.date[1])*1e-9
    lw['time'] = (lw['date']-lw.date[1])*1e-9
    ra['time'] = (ra['date']-ra.date[1])*1e-9
    la['time'] = (la['date']-la.date[1])*1e-9
    return [rw_t,lw_t,ra_t,la_t,s1,s2]
```

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Critical Care

RESEARCH LETTER Open Access

Visualisation of limb movements by accelerometers in sedated patients

Erlend Flinstad Harbo[1], Silje S. Fuglerud[2,3] and Nils Kristian Skjærvold[1,4*]

Dear Editor,

The prognostication of neurological outcome in sedated ICU patients is challenging. Multiple clinical scoring schemes and examinations are used, where different motoric responses are important input variables. Accelerometery is a well-known technology widely applied in different fields of research and everyday electronic products. In medical research, accelerometers have been used in longitudinal epidemiological studies of physical activity and health as well as in ICU studies on the topic of activity, sleep and agitation monitoring. Similarly, accelerometric information could be a candidate to improve future neurological prognostication schemes. To the best of our knowledge, including a systematic review from 2015 [1], there are no published articles on automatic motion registration from ICU patients in connection to neurologic outcome prognostication.

We investigated a small population expected to experience motoric changes over a limited time period. After institutional approval and patient consent, we connected four wireless 3D accelerometric AX3 sensors (Axivity Ltd., Newcastle, UK) to the limbs of 10 post-cardiac surgery patients in the cardiothoracic ICU while still in general anaesthesia. We collected accelerometric data and observed their limb movements as the sedation was pre-described and the patients woke up. Movement artefacts induced by the health personnel were kept at an absolute minimum.

The raw data sampled at 100 Hz mandates processing before providing sensible information. The three-dimensional acceleration vector for each extremity was combined into one according to

$$A = \sqrt{x^2 + y^2 + z^2} - 1.$$

A peak finder function was applied with height $50\sigma + \mu$, where σ was the standard deviation and μ the mean of the first stabilising period when the patient was fully immobile, set to 2 min. The time-distance of the function was set to 50 samples. The acceleration peaks were summed within 1-min epochs to visualise the movement data as heat maps. This greatly reduces the amount of data that the clinician encounters and eases the interpretation. Finally, all data were truncated to 10 min starting at least 2 min before the first detectable

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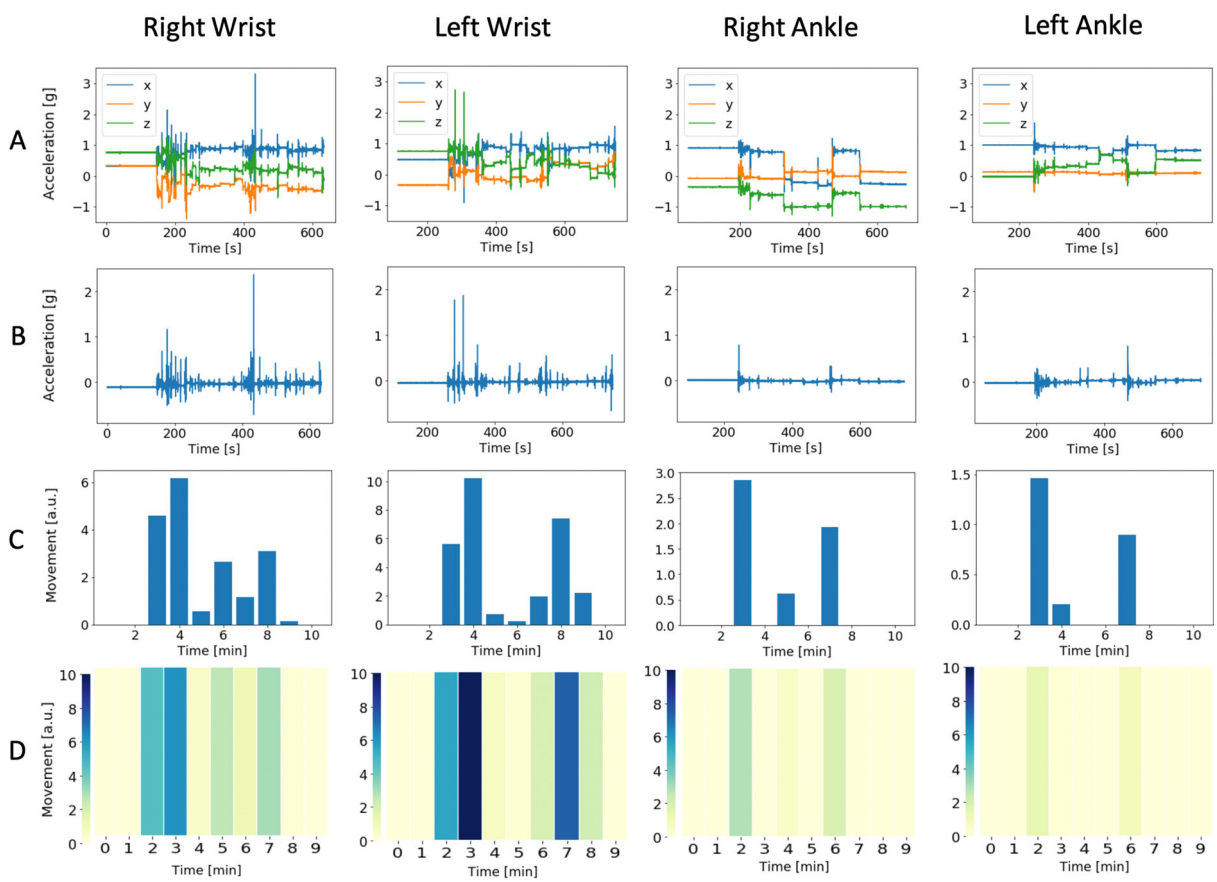

Fig. 1 Example of the stages of data and graphical processing from one study subject, one column for each of the four limbs and the rows according to **a** raw accelerometric data in three dimensions, **b** 3D data condensed to one variable per limb, **c** total amount of limb movement shown as histograms in 1-min epochs, and **d** heat plot of the data from **c**

movement. All analyses were performed in the Python programming language [2]. An example of the stages of data and graphical processing is shown in Fig. 1.

In all patients, this approach detected a change from no limb movements to various degrees of movement in one or several limbs, as shown in Fig. 2. Since the time from de-prescription until wake-up varies substantially between individuals, we highlighted the 10 min with most movements from each patient, including at least a 2-min start period of baseline no movement. Interestingly, all patients went into a motionless period after the wake-up period, visible in the figure. The quantity of movement correlated with our manual observations and was highly individual.

We show the possibility of detecting the amount of movements in sedated patients and to present these data in a simplified manner to the clinician. As such, we are expanding the use and usability of accelerometric data from earlier studies which mainly focused on sedation and agitation levels [3, 4]. In ICU patients, there are several known types of abnormal movements depending on the underlying pathophysiology of brain injury [5, 6]. In this first study, we did not aim at doing any qualitative movement characterisation albeit we do believe this should be possible with the use of accelerometers in the future utilising the full time-resolution of the sensors. It will, however, require more complex data processing algorithms made from larger, labelled datasets including both accelerometric data and clinically validated brain injury diagnosis.

Limitations to this trial are the low number of participants and the choice to study post-surgery patients and not the designated user population of critically ill patients with a potential brain injury.

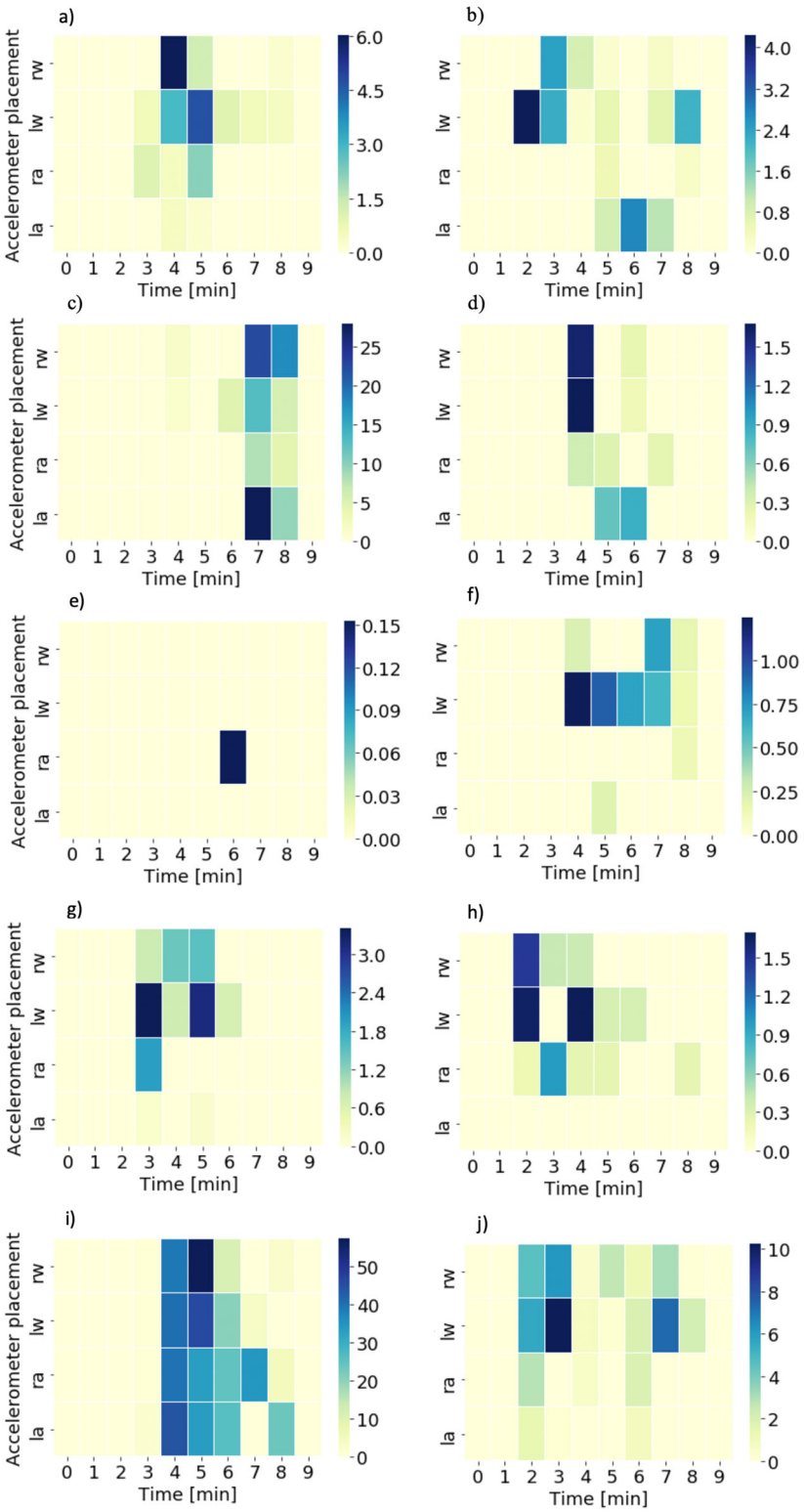

Fig. 2 Heat map of limb movements in all 10 patients (**a** to **j**) with the amount of movement for each limb as a function of 1-min time epochs over 10 min. la left ankle, ra right ankle, lw left wrist, rw right wrist

Acknowledgements
Not applicable

Authors' contributions
EFH designed the study, performed the data acquisitions, performed the data analysis, and drafted and revised the final manuscript. SSF invented and performed the data analysis and drafted and revised the final manuscript. NKS concepted and designed the study, wrote the protocols, and drafted and revised the final manuscript. The author(s) read and approved the final manuscript.

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EFH is a medical student at Norwegian University of Science and Technology while SSF and NKS have scholarships (PhD and postdoc) provided from Samarbeidsorganet Helse Midt (https://helse-midt.no/samarbeidsorganet). In addition, some founding from Trondheim University Hospital was used (purchase of the accelerometers).

Availability of data and materials
The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Ethics approval and consent to participate
In this study, 10 patients scheduled for cardiac surgery were included after institutional ethical board approval (Regional committees for medical and health research ethics, Central Norway, NTNU/REK midt, Det medisinske fakultet, Postboks 8905, 7491 Trondheim; study ID 15128).

Consent for publication
Not applicable

Competing interests
NKS is a cofounder, shareholder, and chief medical officer at Moon Labs, a medical-technological company that is prototyping a sensor intended for bedward monitoring. Moon Labs is not working with biosensor data from ICU patients. SSF and EFH declare that they have no competing interests.

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