MoveHN-A database to support the development of motion based biosignal processing systems

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***Abstract* — In the field of signal processing, pattern recognition and also modeling and simulation, it is often necessary to use large data sets. These allow reliable, independent and test case spanning development of algorithms or even of complete systems. The data is usually taken from existing data sets such as TIMIT for speech recognition and processing or EPILEPSIAE to develop algorithms for epileptic seizure prediction, to give just two examples. Apart from the fact that some of these databases imply a considerable cost factor and thus are not accessible to all research groups, even greater problems arise if no data is available at all. In the field of speech recognition, this problem was solved more or less by creating databases. In the area of biosignal processing with a focus on the functionalization of furniture for care and clinical facilities, there is still a need for large data sets. This was also the case with biomechanical modeling of functionalized furniture, since up to now none or few data on the human movement sequences were available. In order to overcome this deficiency, the following paper presents a new database of motion patterns, which is intended to support the development of algorithms for motion detection as well as modeling biosignal processing. The database can be used and downloaded by any interested researcher for free.**

Keywords — Biosignal processing; model driven development; biomechanical modelling; motion pattern database; modelling;

I. INTRODUCTION

In 2015 a report published by a large German health insurance fund has already explicitly pointed out [1] that the current forecast for the number of people in need of care in the Federal Republic of Germany in 2060 has been too low by more than 220,000 persons. Thus the society expects 4.52 million people in need of care in Germany solely at that time. This number is significantly higher throughout Europe. In addition to the aging society, critical and chronic diseases of civilization are also a problem, which is increasing rapidly in recent years. These developments result in very high requirements for the hospital and care sector such as better training and good physical fitness of nursing staff. Additionally an increasing number of trained staff is required, which implies enormous cost pressure to cover the demands of an increasing number of healthcare patients. In addition, a constant or falling number of nursing staff has to be taken into account. It is therefore necessary to work on alternative approaches that provide support for patients and nurses. So, the focus in the field of geriatrics must be on prevention by means of long-term monitoring in order to be able to recognize and react to deterioration in the patient's condition at an early stage. A forward-looking approach to assist people in need of care and to carry out long-term monitoring is the support through functionalized furniture. Technological basis is the preparation-free derivation of patient parameters using sensors integrated into domestic or clinical furniture. A breakthrough in this research was made by Koivistoinen et al. 2004 [2] in the realization of a ballistocardiographicaly screened "functionalized" chair for deriving heart activity. The system is based on an electromagnetic film sensor (EmFi). Further application examples are shown by Kim et al. [3] integrating an EmFi sensor in a wheelchair to carry out long-term measurements as support for people with disabilities. Functionalizing (nursing) beds would be a more useful approach to perform a preparation-free long-term monitoring. Advantages of measuring systems in such beds are the universal applicability on the one hand and the relatively long duration of patients' stay in bed between six to eight hours daily on the other hand. Furthermore, in this type of measurement system, disturbances in the signal by e.g. speaking, eating, additional movements, etc. can be excluded more or less. In this field of research there are different approaches. Shin et al. [4] presented an air mat based sensor system and Zhu et al. [5] used a sensor system under the pillow in nursing beds. Beattie et al. described a system using force measurement cells under the bed feet to classify critical breathing events [6] in the form of central apnea and obstructive apnea / hypopnea. Other systems are used to recognize human body postures in nursing beds to detect motion [7] or to analyze different states during sleep [8]. Furthermore, it is possible to predict the risk of decubitus pressure sores [9] or fall out of nursing beds [10]. A major problem is the mostly empirically driven development. Frequently, data sets of test persons are missing in sufficient numbers to enable a statistically independent development. Further challenges are time and personnel consuming

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acquisition and creation of the data as well as the fact that it is ethically and morally unacceptable whether old and frail people should be addressees of the systems and serve as data basis. In addition, there is a strong dependency between the quality of the signal and the body posture, especially in systems where the person is standing or sitting during measurement (Javaid et al. [11]). In order to compensate for many of these disadvantages, the authors propose a model-driven development. For this purpose, the preparation-free measuring system can be modeled and, depending on the extent of the model, many points can be tested and verified at an early stage of development. However, even with a model-based development approach, the missing data from real test persons cannot be replaced. For this reason, a new database of motion data is presented. The data can be used as a basis for the investigation of human movement patterns in the field of biosignal processing, pattern recognition and modeling. The paper is organized as follows. First, we briefly describe the application for which the database data was created. Subsequently, the details of the database as well as the generation of the data are introduced. Finally, the download options as well as an outlook are presented.

II. Model Driven Development

Our research is based on a model-based development of a functionalized nursing bed. The laboratory prototype used for the research consists of a commercial nursing bed that has been functionalized with two commercially available force measuring systems. The sensor setup is shown in Figure 1.

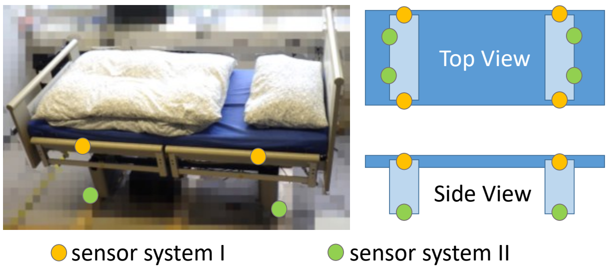

Figure 1: Laboratory prototype "functionalized nursing bed"

The setup is divided into two independent parallel force sensor systems I (Bosch) and II (Zemic) to detect the load weight and temporal mass changes within the bed. The prototype is presented in detail in [12], so no further details are given at this point.

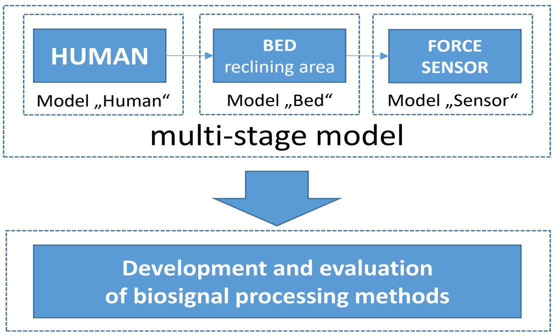

Figure 2: Schematic representation of the multi-stage model

As initial patient parameters, the center of mass, the weight of the person in bed, the bed occupancy, an indicator of unrest and the current respiratory rate [13] are derived from the sensor signals. In addition, an HMM based recognition system was developed to derive different body postures and actions of a human being in the nursing bed [14]. During the development of different methods and algorithms, it quickly became clear that additional references to evaluate the developed algorithm were missing. For this reason, the development of a multi-stage biomechanical model was initialized. The basic principle of the model is shown in Figure 2. In our model, the human being, the furniture and the sensors are modelled in three stages in order to be able to use a reference as precise as possible in form of a model. An advantage of this method is the possibility to modify and adapt every part of the model independently. All simulation steps are carried out and calculated with Mathworks Matlab and Simulink. The multi-stage model approach is also presented in detail in [12]. Modelling is always a compromise between realistic representation and necessary effort in the form of series of measurements or test data. Since our model has three different stages, the first stage, the human itself, should be presented as realistically as possible in order to avoid subsequent errors in the two downstream stages. So, the first part considers different body parameters (body dimensions weight, height and width, cardiovascular and respiratory elements (heart rate, breathing rate and the caused mass shift), movement and body position (initial and after the movement)). The body dimensions are modelled with regard to anatomical models [15, 16]. The body model is built as a so-called stickman model in which the body dimensions were taken into account. Initially, a linear movement of limbs and torso was assumed. Through this, it was possible to create artificial body postures and actions. But compared to real body postures and actions, the modelled movements seems to be very "robot" like. This is also evident in the direct comparison of the electrical signal sequences of the four sensors of each sensor system and the simulated signal profiles of the model. To solve this issue, the following database was created.

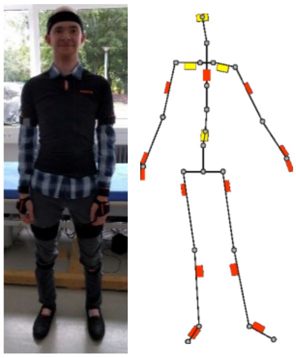

Figure 3: XSens system attached to a test person (left) and overview of the different sensors (right)

III. MoveHN - A database to support multi-stage modelling

Detailed information on human movements can usually be found in medicine and sports science. Unfortunately, these representations, are often very theoretical. However, in order

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to investigate the movement patterns of real people and later to use them in own developments, a database with data sets of a markerless motion tracking system was created. The XSens MVN Awinda System was used for this purpose. In the area of biosignal processing and modeling, the XSens system is well known and has already been used in other works, e.g. for gait analysis [17] or motion strategy analysis [18]. The XSens Awinda system consists of 17 cordless trackers attached to straps. An example is given in Figure 3. On the left side, a test person with a completely installed sensor system is shown, on the right side the corresponding sensors are shown on a stick man. The red areas on the right side of the image represent sensors that are attached to the front of the human body, the yellow areas are sensors attached to the back. The system is actually aimed at users in the area of animation and is characterized by the fact that it is a very small and robust system, which allows tracking of the full body and related movements. The sampling rate of the portable system is 60 Hz, the battery life lasts about 6 hours. The sensors are connected via special XSens protocol that is based on IEEE 802.15.4, around 2.4 GHz to the Awinda station. The data acquisition is done via XSens MVN Studio Software. All sensors are synchronized with an internal update rate of 1,000 Hz. The software provides measured values for linear acceleration, angular velocity, magnetic field, sensor orientation and in addition it is possible to calculate individual positions of 23 model body parts, e.g. head, shoulder, spine, pelvis, arms and legs etc. A big advantage of the system is the XML-based file format in which the collected data is available, thus facilitating further processing of the data. Through wireless transmission technology of the sensor signals, the system can also be used without problems in unusual locations, for example within a nursing bed and with various positions and movements. Further details on the XSens system are not shown at this point, but can be found in [19]. As previously described, the focus of the data set is on movement sequences and body positions of people in nursing beds. To use the data later e.g. for modeling, corresponding movement sequences were defined. A total of 680 files, approximately 400 minutes, of motion data were recorded.

	Posture / Action	Description
1.)		Empty bed
2.)		Sit down/ Stand up
3.)		Supine, center of the bed Arms and legs streched out
4.)		Supine, center of the bed Arms and legs close to body
5.)		Crouched sitting, Center of the bed
6.)		Lateral position, Rightmost/ Leftmost position
7.)		Restlessness, Turning back and forth

Figure 4: Example for postures and actions in the database

These were divided into data from five male and five female test persons, each with two recording sessions on two different days. The age of the test persons is in a range of 23 to 30 years, the weight is in a range of 67 kg to 114.1 kg and the body size is in a range of 156 cm to 184 cm. 20 different actions and nine different body positions were taken into account. An overview of some of the actions and body positions is given in Figure 4. The group of test persons does not correspond to the actual target group of persons above 65 years of age. However, it is nevertheless useful to record data from younger people, as we need motion sequences that are more like the norm of a movement process. Older test persons may already be restricted in their movement. Furthermore, it is ethically or morally unjustifiable to use persons who are already restricted in their movement for testing. Every test sequence is designed in such a way that the test person changes from body position A via an action to body position B and then returns to body position A again via an action. The duration is not predetermined in this case in order to ensure a natural course of the body movements and the body positions. The sequence is illustrated in Figure 5.

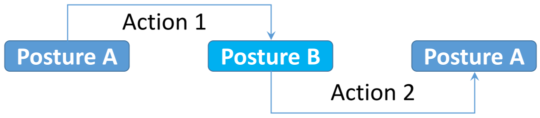

Figure 5: Test sequence for every record

For example, the typical "go to bed" sequence can be described with the postures and actions 1, 2 and 4 in Figure 4. In illustration 6, a movement sequence of a record from two different test persons (red and black stickman) is shown as an example.

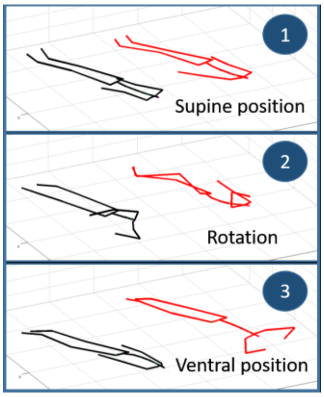

Figure 6: Plot of two persons' movements: "supine position (1), rotate (2), ventral position (3)"

The persons in part 1 are in supine position, then turn in part 2 over to right or left side and then in part 3 they are in ventral position. Even in these very basic representations it is easy to see that the movements of a person can be very different in detail. In order to be able to further process the recorded data, all data records were provided with corresponding temporal descriptions, so-called labels, in a semi-automatic process. For this purpose the acceleration data of the sensors were roughly divided by means of an energy measure. In a further step, the subdivision was manually edited and improved. A corresponding labeling tool was developed with Matlab as support.

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IV. Distance Measure for Comparing Data Sets

It was of great interest for further use of the data to find a measure of how far each of the 23 model part elements describing an entire body and its movement differed between individuals with the same position or action. In order to be able to compare the different motion sequences, an appropriate distance measurement is required. The distance measure should be elastic because a rigid distance measure such as, for example, the Euclidean distance, cannot reasonably take into account differences between the motion sequences from stretching or displacement with respect to the time axis. A suitable elastic distance measure for this task is the so-called "Time Warp Edit Distance" (TWED). Simply described, TWED calculates the distance δ from two time series by deleting data points from one of the time series to be compared, in order to match them in sections of the other. The higher the cost of deleting or the more distantly supposedly suitable data points are, the more dissimilar are the time series. TWED is used as a distance measure for discrete time series and, in comparison to distance measures like DTW, TWED is a metric. It was first proposed in 2009 by Marteau [20]. The corresponding formalistic description to calculate distance δ is:

$$\delta_{\lambda,\nu}(A_1^p,B_1^q)=\mathrm{Min}\begin{cases}\delta_{\lambda,\nu}(A_1^{p-1},B_1^q)+\Gamma(a_p'\to\Lambda) & \text{delete A,}\\ \delta_{\lambda,\nu}(A_1^{p-1},B_1^{q-1})+\Gamma(a_p'\to b_q') & \text{match,}\\ \delta_{\lambda,\nu}(A_1^p,B_1^{q-1})+\Gamma(\Lambda\to b_q') & \text{delete B,}\end{cases} \quad (1)$$

With:

$$\begin{aligned}\Gamma(a_p' \to \Lambda) &= d_{LP}(a_p,a_{p-1}) + \nu\cdot\left(t_{a_p}-t_{a_{p-1}}\right)+\lambda,\\ \Gamma(a_p' \to b_q') &= d_{LP}(a_p,b_q) + d_{LP}(a_{p-1},b_{q-1}) + \cdots\\ &\quad \ldots\ \nu\cdot\left(\left|t_{a_p}-t_{b_q}\right|+\left|t_{a_{p-1}}-t_{b_{q-1}}\right|\right),\\ \Gamma(\Lambda \to b_q') &= d_{LP}(b_q,b_{q-1}) + \nu\cdot\left(t_{b_q}-t_{b_{q-1}}\right)+\lambda.\end{aligned} \quad (2)$$

The recursion is initialized as follows:

$$\begin{aligned}\delta_{\lambda,\nu}(A_1^0,B_1^0) &= 0, &&\\ \delta_{\lambda,\nu}(A_1^0,B_1^j) &= \infty && \mathit{for}\ j\geq 1,\\ \delta_{\lambda,\nu}(A_1^i,B_1^0) &= \infty && \mathit{for}\ i\geq 1,\\ \mathit{with} & && a_0' = b_0' = 0\ \mathit{by\ convention}\end{aligned} \quad (3)$$

TWED permits the calculation even of minimum differences in movements and body positions, e.g. pauses in motion or comparable movements with different duration. The distance values in Figure 7 to 9 were normalized to the respective length of the data set. If the sequences are absolutely identical, the distance δ is 0. Otherwise, the distance value is between zero and one, one indicating a total difference in the data. In order to provide an overview of the differences in the movement data, the distances for the data of the three test persons "FK", "AK" and "TB" were calculated and compared as an example. In order to show that even the movement sequence differs from the same person, the datasets of the test person FK from both sessions, which were carried out on two different days, were compared. For this work, λ = ν = 0.5 was selected. The parameters of the test persons are shown in Table 1. In the selection of test persons from the database, care was taken that the body size as well as the age is approximately the same while the body weight strongly differs.

Table 1: Body parameters of different test persons

	Testperson		
Name:	**TB**	**FK**	**AK**
Age:	28 years	28 years	26 years
Weight:	68.8 kg	114.1 kg	88.9 kg
Height:	1.84 m	1.84 m	1.80 m
Gender:	male	male	male

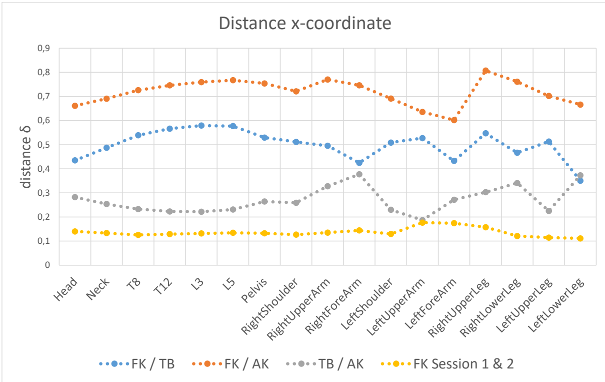

Figure 7: Distance δ for FK, TB and AK – x coordinate

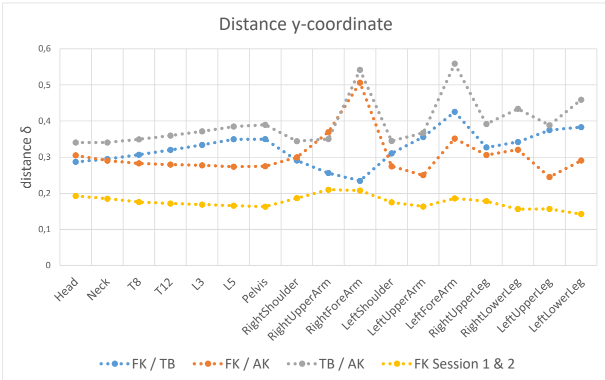

Figure 8: Distance δ for FK, TB and AK – y coordinate

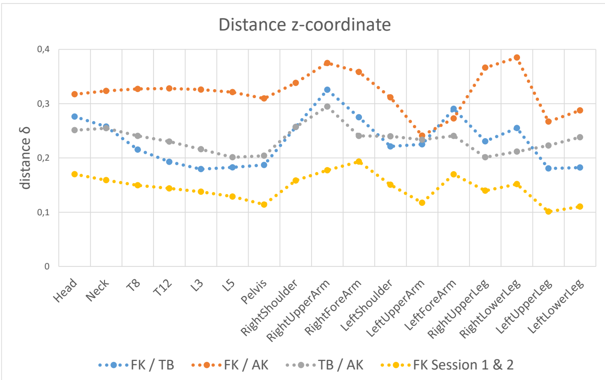

Figure 9: Distance δ for FK, TB and AK – z coordinate

The deviations of the coordinates for the movement sequence "supine position, rotation, ventral position, rotation, supine position" are shown in Figures 7 to 9. For a better overview, only 17 of 23 elements of the stickman are shown, elements like hands, feet and toes are omitted. The individual distance values δ are to be regarded as discrete for each part of the body. For a better overview, the points for a data series were connected to a dashed line. Furthermore, for the sake of clarity, the distance values for the region of the head and the torso are shown in the left half of the Figures; the extremities are correspondingly shown in the right half. It can be clearly seen that the two lighter-weight persons have in many cases a smaller deviation in their movements relative to the torso. Looking at the movements of the arms and legs, a relatively large difference can be observed in all three persons. This was also to be expected, considering the position shown in Figure 6, Part 3. The slightest deviation results as expected when comparing the sessions of test person FK which were recorded on two different days. But also here a clear difference in the data is visible. This is due to the degrees of freedom (position in the bed, movement sequence not exactly defined and reproducible) of the experimental series.

V. Conclusion and Outlook

The new database MoveHN was presented in this work. The database is freely available to other researchers and can be used to develop own algorithms and systems in the field of biosignal processing. In this context, particular attention was paid to movement processes of a person in a nursing bed in order to be able to use the movement patterns for the development of methods for biosignal processing and modeling. In summary, the database contains 680 files with movement sequences of a total of ten persons. Furthermore, the database was provided with additional temporal descriptions to allow universal use of data. In order to be able to better classify the individual motion patterns, it was shown that the differences can be calculated in form of a distance measure between individual data sets. A comparison of the distances δ shows that there is great variability between data sets. Therefore, the real data is necessary for further research since the problem of the modeling of motion sequences cannot be solved by simple linear assumptions. It is useful to further expand the data set. With regard to the research work of the authors, the data of MoveHN is used to calculate average motion sequences for the already presented multi-stage model. The biomechanical model is further improved based on the mean motion data from MoveHN. The procedure for calculation of mean motion data will be presented and discussed in subsequent papers.

VI. Download

The entire MoveHN database is subject to the Creative Commons (CC-BY-NC-SA) and is available for download at: http://ami.kr.hs-niederrhein.de/moveHN

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