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The Overview of Challenges in Detecting Patients' Hazards During Robot-Aided Remote Home Motor Rehabilitation

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Abstract:
Minimally-supervised home rehabilitation has become an arising technological trend due to the shortages in medical staff. Implementing such requires providing advanced tools for automatic real-time safety monitoring. The paper presents an approach to designing the mentioned safety system based on measurements and modelling the interface between a patient's musculoskeletal system and a rehabilitation device. The content covers the segmentation of patients regarding their health conditions and assigns them suitable measurement techniques. The defined groups are described by the hazards with which they are most endangered and their causes. Each case is correlated with the appropriate data type that may be used to detect potential risk. Moreover, a concept of using presented knowledge for tracking the safety of bones and soft tissues according to the biomechanical standards is included. The paper forms a set of guidelines for designing safety systems based on measurements for robot-aided home kinesiotherapy. It can be used to select an appropriate approach regarding a specific case; which will decrease costs and increase the accuracy of the designed tools.

Keywords: *Biosignals, Biomechanics, Home rehabilitation, Kinesiotherapy, Minimally-supervised treatment, Rehabilitation robotics*

1. Introduction

Kinesiotherapy is treatment with motion designed to restore maximum functionality of patients. Its purpose is to recover from diseases of the musculoskeletal system. During kinesiotherapy of extremities, a physiotherapist interacts physically with the patient's limbs in a specific way to regain their mobility [61].

Bringing back maximum functionality is essential for basic daily activities (ADL). The motor treatment often requires a lot of professional physical engagement, which may be overtaken by rehabilitation robots. Moreover, working with people who do not have the ability to sit or stand themselves often requires upright standing with the help of up to three physiotherapists [21]. In addition, the ageing society requires more intensive and frequent treatment while the number of medical personnel ongoingly decreases. Hence, the most significant problem is an insufficient number of physiotherapists and caregivers in nursing homes [50]. It is possible to reduce the participation of professionals in the therapy even while being dependent on family members. However, this requires the devices to support performed exercises in a precise and controlled way [53]. Research indicates advantages of providing stroke patients and people with paresis, who require permanent rehabilitation, with transportable, lightweight, and wearable devices. Such may be involved in the post-discharge home rehabilitation [60].

Due to the COVID-19 pandemic, patients needing constant therapy were severely disadvantaged. This was caused by pandemic restrictions in human meetings [25], overcrowding of hospitals, and the shortage of health care members. To avoid such situations, it is crucial to develop well-validated tools for remote home rehabilitation [26].

Considering the mentioned conditions, adapting rehabilitation devices to home self-use is an arising need and challenge for medical robotics. As the therapist may be not provided with haptic feedback during remote home rehabilitation, developing a robust safety system is critical [80]. Such should analyse dynamics of the rehabilitated body segment and additional measurements to assess the safe operation of a user without involving a physiotherapist [23]. The following paper presents an approach to modelling patients' physical loads to detect potential pain or discomfort automatically. This is possible for particular cases by measuring and interpreting biosignals or dynamic parameters. The paper classifies patients according to their disorders level. Based on these levels, potential hazards during kinesiotherapy are listed and matched with the corresponding measurements. These may be used to build a model enabling continuous human-less safety monitoring.

2. Methodology

Based on a literature overview, the paper consists of a systematic analysis of the potential automatic detection of hazardous situations during remote home treatment. This includes disease case segmentation, possible causes of injuries, and measurement methods. With these, a multibody model may be created and used to assess the safety of the treatment.

The Scopus, Research Gate, Google Scholar, and PubMed databases were analysed to create this paper. The following keywords were used: home telerehabilitation, kinesitherapy, stroke, paresis, spasticity, extremity exoskeleton, pain detection, measurable biological signals, ROM measurement, OpenSim. 92 articles were reviewed with the limitation of being published in 2016 or later, of which 37 were considered not to contribute much to this paper. Papers describing the exact concept of specific rehabilitation devices were rejected. However, it is worth noticing that most of them assume the constant presence of a physiotherapist next to the patient or prior limiting joints range of motion (ROM), which affects the device's working area. Papers mainly dealing with the pharmacological treatment of strokes, spasticity, or paresis were also rejected, as this is not relevant for the uptaken topic.

3. Results and Discussion

3.1. Segmentation of Cases

The patients were segmented into five groups to assign them corresponding potential risks. Thanks to this, the number of measurement techniques needed for safety monitoring is limited for every case. The defined groups are :

1) Patients with sensation after mechanical trauma (e.g., fractures) or light musculoskeletal disorders (e.g., joint calcification) and post-surgical patients – with a possible complete return to pre-injury performance
2) Patients with flaccid muscles, deprived of sensation
3) Patients with flaccid muscles, with sensation
4) Spastic patients, deprived of sensation
5) Spastic patients, with sensation

The patients with muscle flaccidity are understood as the ones with missing connections between the brain and spinal cord circuits essential for voluntary movement [22]. Spasticity is a motor disorder characterized by a velocity-dependent exaggeration of stretch reflexes resulting from abnormal intraspinal processing of primary afferent input. Such malfunctioning implies increased muscle tone, enhanced tendon reflexes, and extended reflex zones [14] and is usually the result of stroke [8]. To correctly refer to individual cases in the paper, they are assigned with the numbers of the above-proposed segments.

The division above includes cases of patients eligible for robotic home rehabilitation and refers to the part of the body rehabilitated (e.g., while performing kinesiotherapy of the lower limb of a patient with the flaccid lower half of the body and sensation, they are treated as the group 3 – even though their upper half of the body may be not affected by any disorder). For every group, the signals which can be measured for pain detection purposes were selected. The proposed approach to detect risk prior to patients' injuries by the robotic rehabilitation systems is presented below.

3.2. Methodology of Measurements

Selection of the appropriate approach to measurements prior to and during kinesitherapeutic robot-aided sessions is critical to automating the process. The methods may be combined and used along with each other to improve the reliability of the safety system of the device. Currently, the most common sensors for rehabilitation devices are IMU, encoders, pressure gauges, and EMG sensors. The first two are used to obtain information on the device's kinematics configuration, while the others are for biofeedback [19, 72]. This subsection presents an overview of the considered techniques and correlates them with the segments presented before.

Measurement of the patient's range of motion

Measurement of the patient's range of motion (ROM) is connected with actively exercised joints. The resulted values describe the operational space of the individual body segment, where the exercise may be performed without pain or any risk of trauma. Such measurement may be realised manually with goniometers or with a rehabilitation device itself, e.g., by the SFTR method [31]. Before starting the actual treatment session, the device should launch a measuring module to determine the patient's ROM and adjust the exercise space.

There is no certainty that staying within single joint limits will ensure the patient's safety during complex movements. In other words, the decomposition of a complex motion into the appropriate components in the fundamental planes: sagittal, frontal and transverse, does not have to correspond to the sum of these movements in terms of the muscle loads . Moreover, such a measurement should take place several times the during rehabilitation process to consider potential ROM increase related to the convalescence process [2]. However, this time-consuming process does not fully safeguard further automatic kinesiotherapy. If such a calibration is to be performed without an additional operator of the system, either intelligent algorithms have to sense motion limits or the device must receive equivalent information from a patient. The first approach is difficult to implement for patients with severe neural diseases. On the other hand, confirming the end of possible motion requires the user's capability of physical interaction with the human-machine interface (HMI) or implementation of vocal commands. This implies the need for an excellent command and sound recognition system, potentially with an advanced neural network [37]. These requirements also affect the number of patients who may use the device.

Pulse and ECG measurement

To measure pulse or ECG, the device has to be equipped with the dedicated sensors. As the severe stress related to pain sensations causes the change in readings [71], this technique can be used to detect emergency states of the rehabilitation system. However, the values of resting heart rate and the measurements during exercising vary for individuals [78]. Additionally, the abnormalities may be registered too late for the robot to react before harming the patient. Moreover, the expected accuracy of around 60–80% and no distinction between pain levels may not be enough real-time pain recognition for robot-aided kinesiotherapy [56].

Estimating the strength parameters of tissues

The safety algorithms can be based on the multibody model of the cooperating device and musculoskeletal system. However, this approach requires comparing computed results of loads within individual tissues with their strength parameters different for every person.

The most vulnerable to injuries are tendons and ligaments [42]. For this reason, machines should not exceed the strength limits of these tissues. It is particularly challenging to obtain data on their parameters, such as Young's modulus. The corresponding experimental trials are usually carried out on animals [7] or tissues from the deceased [34], which do not fully correspond to the tissues of alive humans. Moreover, tissue properties change with age, gender, and experienced illnesses [59].

To prevent hazardous situations, estimating the tensile strength is most critical for individual soft tissues, as they are most vulnerable to damage in this direction [3]. Before the treatment, their values may be obtained with a specific device such as MyotonPRO [5]. The measurement method consists of registering the damped natural vibrations of soft biological tissue in the form of an acceleration signal and then calculating the desired parameters. Such technology enables measuring the tone, stiffness, flexibility, relaxation, and creep of tissues [5]. The proposed solution could also be transferred to the rehabilitation robot by equipping it with a dedicated sensory system. Nevertheless, there are also limitations to this measurement technique, e.g., the results are less accurate for obese patients as well as the deeply located and too thin tissues are difficult to work with [1].

EDA measurement

EDA is electrodermal activity, demonstrated to be effective in arousal estimation [73]. As a patient's sweating changes at times of severe stress [32], analysing correlated EDA signals can contribute to detecting increasing pain. This technology is being continuously developed, and it does not have many validated applications yet [4]. There are serious doubts whether emotions such as joy or stress caused by providing treatment by a robot, not a human, will not cause excessive sweating [64]. Such an effect can lead to confusion of hazard situations with a regular operation of the device by the automatic safety monitoring system. For this reason, implementing EDA within a real-time system for detecting risks in home robot-aided treatment is not suggested.

EEG measurement

EEG, electroencephalography, is a non-invasive method of analysing brain electrical activity based on the recordings from the scalp. As a patient's intentions are detectable with this measurement [46], a rehabilitation robot can use EEG signals for predictive control to interact with a user and not exceed their range of motion [80]. However, not every intention of motion results in the movement – its image may be enough for the corresponding area of the brain to become active [49]. On the other hand, researchers proved that physical pain, particularly acute [70], can be detected based on EEG with an accuracy of almost 95% and used for real-time reflex in prostheses [75]. This implies the applicability of the technique for robot-aided rehabilitation. Nevertheless, using advanced EEG systems is relatively expensive and requires precise placement of the electrodes on a patient's scalp to provide repetitive results [12]. These might be the main barriers to using such for home therapy.

EMG measurement

EMG, electromyography, may be either an invasive or non-invasive investigation of the electrical activity of muscle units or whole groups. Registered signals provide information regarding the temporal behaviour and morphological layout of active motor units during muscle contraction [68]. This may be used to estimate internal stress in these tissues and compare them with their biomechanical limits. The safety system must react to sudden peaks in the registered signals. These may either be related to the nociceptive flexion reflex caused by pain stimuli or the spastic reflex caused by a sudden noise, unexpected touch, or stress [13]. The two mentioned have to be distincted. Hence, the EMG may be useless for detecting hazardous situations for spastic patients in spasticity-related situations. The researchers also present the method of detecting pain based on EMG-registered facial expressions. However, this requires non-affected facial muscles and generates similar problems as for EEG, including precise placement of the electrodes [39]. The values registered with EMG can be used to estimate temporary muscle tension [58]. However, the surface EMG, the only applicable within robot-assisted home kinesiotherapy, is vulnerable to noises from electrical devices, other muscle groups, and fat layers [77].

Selection of methods for cases

In order to propose the solution tailored to the capabilities of a specific group of patients, a decision tree for measurement selection is presented in Figure 1. The first step is to assess whether a patient has physical sensations. It is assumed that post-trauma patients meet this requirement – if not, they are assigned to groups 2 or 4.

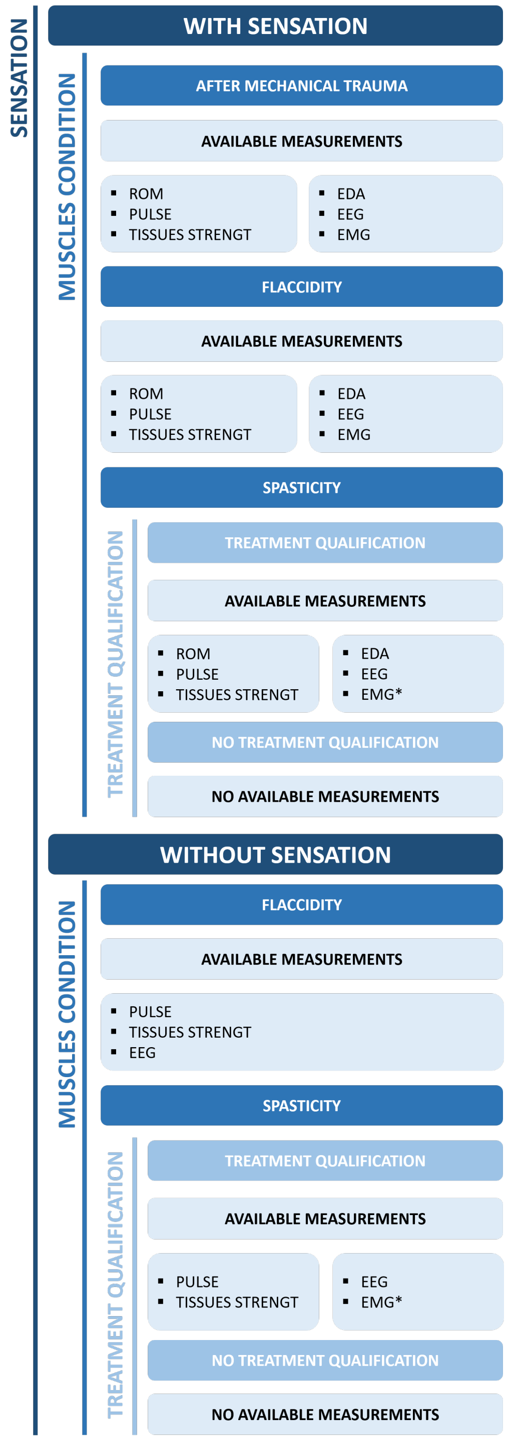

Figure 1. Segmentation of cases with corresponding measurement techniques

Moreover, patients with spasticity have to be medically qualified for robot-aided exercising. This decision depends on the severity of the problem according to one of the scales such as Ashworth score, modified Ashworth score, Tardieu scale, or modified Tardieu scale [74]. The ones with the degree of spasticity exceeding a certain threshold cannot workout by themselves due to their spastic, uncontrolled, intense muscle contractions [14]. Such a pre-treatment medical assessment should be based on several doctors' independent, expert opinions [35].

On the other hand, patients deprived of sensation often suffer from excessive sweating [33]. They are unable to identify their own pain ailments [33], and thus, their available range of joint mobility.

As may be observed in Figure 1, patients from group number 1 are suitable for all the measurement methods. The most challenging task is to measure biological signals for group 2 because it is not possible to gather data related to their muscle tension or their sense of motion limits.

Moreover, there is a difference in the applicability of EMG measurements between non-spastic and spastic patients. For the first group, the sensed electrical signals may be correlated with the muscular forces and then analysed regarding biomechanical limits for safeguarding purposes. When it comes to the second group, their uncontrolled, rapid, and severe muscle contractions may turn EMG signals unable to be used as described above. However, significant changes in the measured signals can be assigned to the emergency stop of the rehabilitation device (marked in Figure 1 as EMG*). This may counteract the hazard of muscle ripping during the involuntary, disease-related contraction. Furthermore, for patients without sensation, the ROM range cannot be measured as they cannot feel their physical limits.

Besides the mentioned above, it is necessary to be aware that for individual cases falling into one of the proposed segments, assigned measurements may not give expected results. Therefore, the patient should be treated as fitting another group, even though they do not meet its criteria.

3.3. Harmful Situation Types

Apart from avoiding a user's discomfort, the automatic safety system for rehabilitation robots should prevent situations causing physical damage to tissues. This may be realised by modelling the causes of particular hazards and comparing their real-time values with estimated thresholds. Table 1 contains segmentation of these. If the risk of a particular cause occuring is typically neglectable during robot-aided treatment, the "high-risk groups" cell is labelled as "low risk".

The bone-related traumas are typically hazardous for the patients rehabilitated after similar traumas. Regarding segment 1 of patients, it is similar for the injuries of muscles, ligaments, and tendons. Therefore, high-risk group 1* refers to the person after similar fractures or damage to the soft tissues. On the contrary, B4 trauma may only appear during long-time force applied to the extremity's segment, which is noticeable as a pain stimulus by patients with unaffected sensation. The device may be stopped immediately in such a situation and not cause any harm. Only groups 2 and 4 are not able to notice such a case themselves. Therefore, an additional safety system monitoring continuous loads has to be provided.

Table 1. Segmentation of tissues damages

Trauma	Symbol	Cause	High-risk groups	Measurement technique (other than tracking device's dynamic parameters)
Transverse bone fracture	B1	Impact transverse force [81]	1*	–
Spiral bone fracture	B2	Impact twisting moments [54]	1*	–
Greenstick bone fracture	B3	Impact transverse force [10]	1*	ROM
Stress bone fracture	B4	Continuous force [30]	2, 4	ROM
Oblique bone fracture	B5	Impact force at an angle [29]	1*	–
Impacted bone fracture	B6	Impact longitudinal force [28]	Low risk	–
Segmental bone fracture	B7	Impact transverse force [69]	1* (low risk)	ROM
Comminuted bone fracture	B8	Impact transverse force [45]	1* (low risk)	ROM
Muscle Strain	M1	Impact longitudinal force [82]	1*, 4,5	EMG + pulse + ECG + EEG + ROM
Muscle Tear	M2	Continuous longitudinal force [76]	1*,4,5	EMG + ROM
Muscle Contusion	M3	Impact transverse force [18]	1*, 4,5	EMG + pulse + ECG + EEG + ROM
Ligament strain	L1	Impact longitudinal force [67]	1*, 2,3,4,5	EMG + pulse + ECG + EEG + ROM
Ligament rupture	L2	Impact longitudinal force [67]	1*, 2,3,4,5	ROM
Tendon strain	T1	Impact longitudinal force [57]	1*,4,5	EMG + pulse + ECG + EEG + ROM
Tendon rupture	T2	Impact longitudinal force [67]	1*,4,5	EMG + ROM

The device has to react to the risk of bone fractures before an actual dangerous situation appears. Therefore, no pain-based measurements will be helpful. Instead, the overall system should be monitored based on its multibody model supplied with the measured dynamic parameters. Moreover, greenstick fractures and similar, more complex variants (B4, B7, B8) may appear while exceeding natural ROM. Therefore, this should also be implemented for safeguarding such cases.

As the strains and contusions are less severe than other types of trauma related to soft tissues, they may be detected with pain-based methods. Moreover, they typically appear preceded by noticeable physical discomfort. Therefore, the device may be stopped before harming the user. For muscle tears and ligament or tendon ruptures, the system has to react prior to the contusion. Hence, a prediction based on the multibody model and measured dynamic parameters of the device is suggested.

Moreover, as the majority of muscles' and ligaments' traumas (not M3) are related to the force generated in the corresponding muscles, they are relevant only for non-flaccid patients. Furthermore, their risk may be tracked with EMG. For the patients with no sensation, an additional system based on the multibody model and the device's dynamics parameters has to be provided.

The damage to soft tissues may also be caused by exceeding the individual's anatomical limits. Therefore, constant monitoring of the device's configuration related to the measured ROM should be realised.

A person assigned to one of the segments presented beforehand should be assigned to the potential risks based on the "high-risk" column in Table 1. Subsequently, a sensory system and a mathematical model should be built to detect and react to hazardous situations. Thanks to such an approach, a rehabilitation device may implement its emergency routines when risk appears to prevent harm to a user. As may be observed, detecting every possible trauma requires tracking the device's dynamics parameters and building at least a simple multibody model of a physical interface between a machine and a human.

3.4. Applicability of Results

The measurements proposed in the previous section, along with the dynamics parameters of the device (drives' torques and encoders' positions), can be used to build a multibody model of the system. Such can be used to estimate internal forces, torques and stresses occurring in the body segments during a treatment session. These values should remain below the acceptable thresholds, which may vary for individual cases. Assuming correct estimations regarding anatomy, comorbidities, and a patient's medical history regarding available bibliography sources enables the building a reliable safety system. The following section presents the individual tissue strength parameters for various cases.

Methodology of testing

Generally, in material engineering, the leading test carried out to identify the strength properties of a material is the uniaxial static tensile test. The major challenge is to select the testing sample shape. This is due to the fact that soft tissues are prepared postmortem (tissues of blood vessels and skin tissues, among others) and, hence, they are pre-tensioned. Therefore, their susceptibility to deformation makes it challenging to prepare the appropriate fitting of a sample. For this reason, soft tissues are usually examined in the form of a bar [47].

Bones

There is a strong correlation between an individual's gender, age, or bone type and the tissue's strength. For example, loading a woman's radius or humerus with a torque of approximately 61 Nm will cause a fracture with a 50% probability [63]. The differences in the critical values may be as significant as 100 Nm for the critical bending moment of the humerus, depending on the gender. Analysing shear force in this bone, its critical value is 1.7 kN for women and 2.5 kN for men [63].

It is much more difficult to damage the lower limb. The probability of an injury increases outstandingly when the force of 5 kN is exceeded [63]. Within the lower limbs, the fibula is the most vulnerable bone. Its tensile strength is up to ten times less than the femur's [63]. For many applications, the critical bone resultant stress can be taken as 150 MPa [20] and should be scaled according to the individual case. Moreover, extraordinary attention should be given to the weakest bone of the exercised body part.

Muscles

There is a correlation between the direction of muscle tension and its force. Moreover, harm to these tissues is typically caused by the tendons' force, or excessive strain [11]. For this reason, muscles are often analysed with tendons as uniform bodies of average strength properties [41]. Correlated stress-strain curves present that a strain over 0.4 leads to a rapid increase in stress as high as 200 kPa [63]. Moreover, the maximum force applied to the muscle may be calculated as the multiplication of PCSA, and estimated tetanic tension, e.g., 22.5 N/cm^2 for mammalian muscles [51]. This requires measurement of the initial muscle lengths and monitoring kinematics of the extremity during exercises. Home treatment should be realised with a lower effort for the patient's safety. As presented in the literature, monitoring of force occurring in this soft tissue can be realised by building a computational multibody model or analysing their measured excitation [15]. Hence, a potentially dangerous situation resulting from exceptional muscle tension could be detected as the rapid increase of the EMG signal, which leads to reaching biomechanical thresholds.

Tendons and ligaments

The strength and stiffness of ligaments and tendons depend on a patient's age and level of physical activity. The maximum force that can load these tissues for a young, athletic person is estimated as 6.1 kN, while for an older person with a static lifestyle – only 4.6 kN [16]. About 10% – 15% extension of the tendon causes stress beyond the elastic limit [63]. This creates stress of approximately 50 kPa and results in a deformation of 4 mm on average [52]. The force generated in the tissue is then close to 200 N [20]. For elderly people, Young's modulus of ligaments and tendons increases. They are more difficult to stretch and become less flexible. Nevertheless, the elasticity of these tissues guarantees their proper functioning [20].

Moreover, the work state of the tissue is also a critical factor for estimating safety thresholds. Contracting tissues generate more stress and are more exposed to the damage than the extensing ones [20]. In general, Young's modulus of the tendon may be estimated as 0.9 – 1.4 GPa [20].

3.5. Model Proposal

As mentioned before, the properties of tissues differ among individuals. The solution to predict the effects of a given exercise for a specific person is to create a digital twin of the patient and a rehabilitation device [27, 80]. It is possible to build such a mathematical model in open software, e.g., OpenSim. The geometrical parameters of the free models may be modified, as well as the strength parameters of the tissues [65].

Modelling the physical interface between a rehabilitation device and a user enables the prediction of the system dynamics in real-time. Hence, hazardous situations may be mitigated before they occur [25]. Moreover, this may contribute to optimising therapy effects.

Internal forces in the tissues may be analysed regarding the external loads applied [62], also in an external environment as the exported time series [44]. Thanks to this, it is possible to simulate the results of the most dangerous movements for patients with particular diseases and a certain age. Based on these simulations, the patient may be qualified only for limited access to the device's functionality. Thus, the home treatment remains safe. Moreover, the registered EMG signals can be included in the model as additional validation of the simulations [55]. However, in EMG-based control, the major challenge is significant signal noise [66]. Due to the need to filter this out, almost real-time processing is hindered. In addition, the measured parameters vary between individuals. Moreover, this type of control can only be used by people capable of generating an electrical activity exceeding a certain threshold [48]. Therefore, the EMG measurements should not be considered a stand-alone tool for automatic pain monitoring.

Within the presented methodology, building an accurate model of the patient and the device is critical for providing the safe operation of the rehabilitation robot. The model's geometry should reflect a real-life patient's anatomy, while the simulated tissues have to be provided with adequate material parameters. The researchers prove that the ready-made open human body models may be effectively enhanced by adding rigid multibody models of the rehabilitation devices and used as proposed in the papers [40, 62, 65].

4. Conclusion

Most of the existing robot-aided rehabilitation systems need the physical presence of a physiotherapist [79]. For this reason, finding a validated context for the presented problem is difficult. Moreover, the methods of real-time safety monitoring based on measurements are not the same for all patients.

During the treatment, physiotherapists manually recognise soft (muscular)and hard (bone) resistance [9]. They know how much to exceed the soft resistance to improve a patient's condition while not exposing them to injury. This haptic feedback with a professional's experience needs to be transferred into machine algorithms. Existing pain scales such as the Visual Analogue Scale (VAS), the Verbal Rating Scale (VRS), and the Numerical Rating Scale (NRS) [38] are subjective. Moreover, they are mainly based on a patient's previous experience compared to the present [43].

On the contrary, the proposed segmentation allows focusing on individual disease entities and developing detection models suitable for specific cases. In the beginning, the robot's aim should be defined. This can either support people after lighter injuries [17] or serve for a gradual recovery of motor activities for people with severe impairment [6].

For the second case, the device may not even correct inaccurate movements initially to regain basic mobility without the pain. Such should be included in the rules for hazards detection algorithms.

Artificial intelligence can be used for these purposes, as it increases the accuracy of therapists' and doctors' decisions. Moreover, the neural networks can contribute to optimal search among the possible ailments causes and treatment options. In addition, this approach is easily scalable. Therefore, it can be used to thoroughly analyse large datasets on the course of the disease and the patient's treatment [19].

Furthermore, rehabilitation devices can be better suited to spastic patients by providing them with a warming-up module involving simple, low-speed motions. This will not only mentally familiarise a patient with the robot but also restrain muscle contractions within the main session [14].

The current challenges in the safety monitoring of robot-aided kinesiotherapy depend on both software and hardware. The former includes the speed of real-time data and the automatic selection of accurately restrained ROM. The systems enabling these have not been implemented in any device yet. The latter consists of the mechanical design requirements to suit people of different anatomy and physically limit the excluded ROM [24, 36].

Therefore, while designing the system for real-time hazards monitoring during the home robot-aided therapy, the following should be validated experimentally:

- how can a muscle tension increased to the pain limit affect the measured signals;
- is the change in the signal related to the hazard confusable with other safe situations;
- how big is the signal-registration and device-processing delay;
- what are the typical values of the measured signal for the individual.

Only selecting the measuring technique, which provides detection of potential risks with high accuracy and low delay, enables real-time monitoring safety during home robot-aided kinesiotherapy. As described in the paper, the methods may be combined, also with a multibody model of the device and the user. Such an approach may become the base for the computing prediction of emergencies and preventing them.

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