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Description de la base de donnée KERAAL de mouvements de rééducation

The Keraal dataset

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Abstract While physical rehabilitation faces the challenge of an increasing number of patients and of a decreasing engagement throughout patients' repetitive efforts, automatic monitoring and coaching of exercises are showing encouraging results in non-medical applications. However, they still have limitations such as errors and limited use contexts. To allow the development and assessment of physical rehabilitation body movements, we identify in this article four challenges to address and propose a medical database of clinical patients carrying out low back-pain rehabilitation exercises. The benchmark performance database includes 3D Kinect skeleton positions and orientations, RGB videos, 2D skeleton data, and medical annotations to assess the correctness and error of each movement. We propose along this dataset, two baseline movement recognition algorithms, pertaining to two different approaches : the probabilistic approach with a Gaussian Mixture Model (GMM), and the deep learning approach with a Long-Short Term Memory (LSTM). This dataset is valuable because it includes rehabilitation relevant motions in a clinical setting with patients in their rehabilitation program, using a cost-effective, portable, and convenient sensor, and because it shows the potential for improvement on these challenges.

Keywords Medical Dataset · Physical Rehabilitation · Human Body Movement Analysis

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0.1 Paper contribution

Our main motivation for creating the presented dataset is to create a robot coaching system capable of supervising a rehabilitation sessions autonomously by providing instructions for each exercise of the program and real-time feedback how to improve the efficiency of the patient's performance such as presented in [4]. We have identified a lack of publicly available comprehensive datasets of physical therapy movements.

We propose in this article a medical database of clinical patients carrying out low back-pain rehabilitation exercises. The benchmark performance database includes 3D Kinect skeleton positions and orientations, RGB videos, 2D skeleton data, and medical annotations to assess the correctness and label errors of each movement. Our Low Back Pain Physical Rehab (LBPPR) dataset introduces four challenges in rehabilitation movements analysis:

1. Rehabilitation motion assessment. The goal is to assess an observed motion sequence by detecting if the rehabilitation exercise is correctly

performed or not. In order to fit real scenarios, only correct demonstrations provided by the dataset are available during training.
2. Rehabilitation error recognition. In other terms, the goal is not only to detect incorrect sequences but also to classify the observed error among a set of known errors, so as to explain and give feedback. Supervised approaches are considered. To tackle this challenge, we provide both correct and simulated errors with associated labels within the dataset.
3. Spatial localization of the error. In addition to recognizing the error, the goal is also to identify which body part is responsible of the error.
4. Temporal localization of the error. The goal is to detect the temporal segment where the detected error occurred along the sequence.

All four challenges are motivated by the need to provide robust, detailed and appropriate feedback to patients during their rehabilitation. The more detailed the feedback provided by the robot coach, the more easily patients can improve their performances. After examining existing datasets with respect to the identified challenges in Sec. **??**, we describe our dataset in Sec. 1. To evaluate our dataset, we report the performance in Sec.**??** of two baseline movement recognition algorithms described in Sec. **??**, pertaining to two different approaches : the probabilistic approach with a Gaussian Mixture Model (GMM), and the deep learning approach with a Long-Short Term Memory (LSTM).

1 The LBPPR Dataset Description

This section describes the protocol and rationale for how the LBPPR dataset was created. It describes the participants included, the hardware setup and the experimental protocol in the dataset. It is made available of the webpage **** [1]

1.1 Rehabilitation program

This prospective, centrally randomized, controlled, single-blind and bi-centric study was conducted from October 2017 to May 2019. It is a part of the **** project. It is a preliminary study to evaluate the supervision of a humanoid robot of rehabilitation exercises for chronic low back pain patients. This study has received a Legal authorisation for clinical tests from the medical ethics board of the hospital at Brest (CHRU Brest). All subjects have given their informed consent to participate in the study. The rehabilitation sessions were carried out within the Rehabilitation department of ***** (hospital) and ****** (rehabilitation center).

1.1.1 Patient care

Patients are first seen in consultation. According to their symptoms and the treatments received, they may be suggested for an outpatient rehabilitation program. If they are, they may be proposed to participate in the clinical trials during the week after their admission to the rehabilitation center, according to the inclusion and exclusion criteria. If accepted, they sign an informed consent.

The whole program lasts 4 weeks. A daily rehabilitation session included physiotherapy, physical activity and balneotherapy lasting in average 3 hours a day. The first week was an observational phase. During this first week all patients are following a common rehabilitation program. At the end of this first week, the included patients performed the evaluation tests and were randomized to be included in the Robot Supervised Rehabilitation Group (RG). They performed 2.5 hours of conventional rehabilitation and 30 minutes of rehabilitation supervised by a humanoid robot per day.

1.1.2 Rehabilitation session

Physical rehabilitation sessions last 30 minutes. Patients are welcomed by the therapist, who have set-up the list of exercises for training. If it is the first session with the robot coach, the patient gets a 5 minutes explanation on how the system interacts with the patient. The therapist then launches the list of 3 exercises through the computer web-interface. At the end of the session, the therapist debriefs with the patient.

1.1.3 The robot coach

Poppy is an open source humanoid robot with a spine of 5 motorized degrees of freedom, arms of 3 degrees of freedom each and legs allowing the realization of low back pain (LBP) program exercises. It's connected to a Kinect camera providing in real-time the 3D position and orientation of the patients' body segments. During the

[1] for the submission, see supplementary material or download from `http://nguyensmai.free.fr/KeraalDatabase.html` for a sample

robot supervised rehabilitation session, the robot first demonstrated the movement to the patient with vocal advice related to the actions performed. Then the patient was asked to perform each movement ten times with the robot supervising and giving feedback thanks to RGB-D Kinect camera information computation (see the demo video[2]).

When training with the robot, participants were given a demonstration of the motion by the humanoid robot Poppy before carrying out the movement himself. The recording starts after Poppy instructs the patient to start, and ends either when it detects that the patient has returned to his neutral/initial position or after a fixed timeout. Having a robot instruct patients on their exercises gives our dataset the advantage of homogeneity of instructions as they have seen in 3D exactly the same live demonstration of movements that they need to reproduce.

1.1.4 Group3 : Healthy participants

For group 3, three healthy adults with no musculoskeletal impairments performed correct execution of exercises and simulated the identified errors described in Sec. 1.4. They are asked to perform each of the three exercises the best they can, but also to simulate the predefined common errors. The participants include a researcher who has witnessed several rehabilitation sessions and two therapists. Their simulation of typical errors can reflect better the true behaviour of patients than lay people. Their recordings took place as one-shot sessions.

1.2 Sensor system

While less accurate than Marker-based motion capture (MoCap), the Kinect can collect and analyse human movement without the constraint of markers. They can be readily used on a daily basis for rehabilitation sessions, without loss of time to position these markers. Moreover, they can easily blend into individual environments, and used in any of the rehabilitation rooms used in the project and do not intrude in participants' activities. As such, vision-based systems have a high potential for clinical applications. This is why we chose to capture the dataset with a Microsoft Kinect sensor for Windows. We obtained the RGB video with the skeleton drawn, and the skeleton joint positions and orientations information. From the RGB videos, we can also obtain a second estimation of joint positions and orientations using the human body keypoint detection library OpenPose [3]. Moreover, for Group3, we also recorded with MoCap using the Vicon system, as they did not use the system on a daily basis. We obtained additionally the joint position and orientation information.

1.3 Exercises and errors

A list of three exercises have been chosen in conjunction with therapists as common rehabilitation exercises that are also used for low-back pain treatment, under the condition that they can be coached by a humanoid robot such as Poppy using visual assessment. Illustrations of these exercises can be seen in Fig. 1 and their videos as exercises 1, 2 and 3 of `http://keraal.enstb.org/exercises.html`. The 3 exercises are centered on spine stretching: a left rotation of the trunk followed by a the same right rotation, a left and right lateral bending of the trunk and a breathing exercise with the upper limbs flexed 90°at shoulder and elbow.

A list of common errors was set up after observation of the patients' performance and in conjunction with the experience of the therapists of CHRU Brest. Errors are illustrated in Fig. 2.

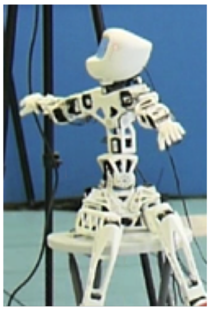
1.4 Dataset annotation

The video collected from patients were annotated by a medical doctor in physiotherapy, using the Anvil video annotation research tool[3].

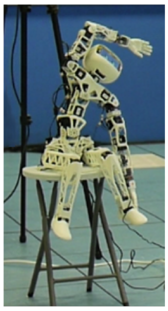
The videos are annotated at three levels related to the four challenges described in Sec. 0.1. On a global evaluation level, an assessment is given as either correct or incorrect (Challenge 1). In the case of an incorrect error, he can indicate if the execution has no errors but finished before the end (label codes 4: incomplete) or the participant did not start the execution of the exercise (label codes 5 : motionless) On the error classification level, in the case of an incorrect movement, annotations first indicate whether the error is significant or small as well as the label of the error (Fig. 2) (Challenge 2). Moreover the body part causing the error is also indicated (Challenge 3). On a temporal level, the medical doctor annotating videos

[2] `https://youtu.be/db1XVXrc-oM`

[3] http://www.anvil-software.org



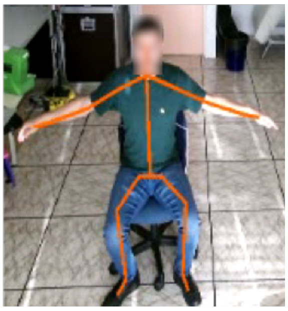
(a) torso rotation (rtk)



(b) flank stretch (elk)

(c) hiding face (ctk

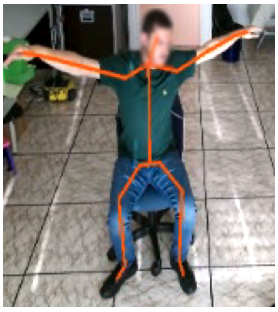
Fig. 1: The three rehabilitation exercises demonstrated by the Poppy robot



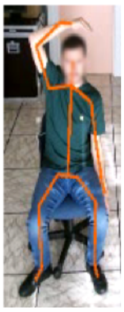
(a) torso rotation – error1:
Arms are not raised enough

(b) flank stretch – error1:
Opposite arm is not along the body

(c) hiding face – error1:
Arms are not raised enough



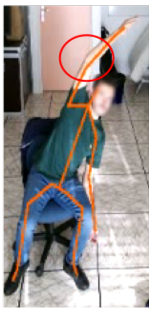
(d) torso rotation – error2:
The torso's rotation is not sufficient



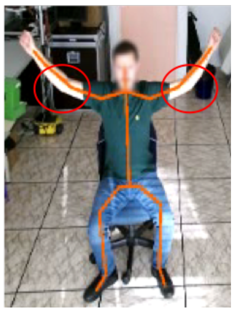
(e) flank stretch – error2:
Body is not tilted

(f) hiding face – error2:
Arms are not outspread enough

(g) torso rotation – error3:
The body is leaned on the side



(h) flank stretch – error3:
The above arm is not bent



(i) hiding face – error3:
Arms are not raised enough

Fig. 2: The three simulated errors for each exercise: each column illustrates 3 errors for each exercise.

can also indicate the time window where the error occurs (Challenge 4), and the same information as previously: whether the error is significant or small, the label of the error, and the body part causing the error.

1.5 Dataset description

Our dataset is composed of :

- Control command files of the robot Poppy to demonstrate the three exercises. They are `json` files that use the syntax commonly used by the library pypot as described in its documentation [4] and can be used with the web-interface developed by the project Keraal to execute on Poppy. They can be used with the physical robot Poppy or its simulation.
- the therapist's annotation in a xml `anvil` format. They indicate whether the execution is correct, the label of the error, the body-part causing the error and the temporal description of the beginning and ending timestamps of the error.
- anonymised RGB videos. The videos are of `avi` and resolution 960x544 for Group3. They are of `mp4` and resolution 480x360 for groups 1a, 1b, 2a and 2b. The resolution was kept low during the coaching sessions with the robot to allow for real-time coaching.
- the positions and orientations of each joint of the Microsoft Kinect skeleton. The `txt` files display in a table, a line per timestamp. The data are presented in ASCII txt format, with space delimiter used for separating the values of positions and orientations of each joint in the order of the skeleton numbering as represented in Fig. 3a.
- the 2D positions of each joint of the OpenPose skeleton in the COCO pose output format. The `txt` files give the x and y positions on each video frame in the format of a dictionary of video frame numbers and joint names[5] (Fig. 3b).
- the positions and orientations of each joint of the Vicon skeleton. The `txt` files display in a table, a line per timestamp.

We have summarized the data and the number of recordings available per participant group in Table 2.

The recordings are organized into the subfolders correspond to each recording modality, and sub-sub-folders correspond to each of the 3 exercise types. In the case of group 3, a 4th level of folders indicate the subject id. The name of the file indicates the label (ex: Error1Bodypart1) of the error and the recording id. The nomenclature of the files in this case is : `group3/Modality/ExerciseName/ParticipantId_label_RecordingId.extension`.

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[4] `https://docs.poppy-project.org/en/programming/python.html`

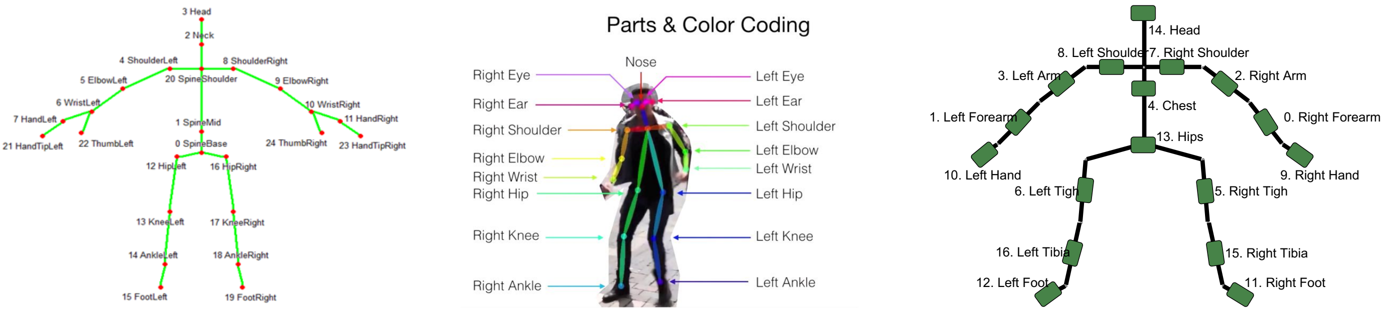
[4] `https://github.com/GRLab/Poppy_GRR`

[5] `https://github.com/CMU-Perceptual-Computing-Lab/openpose/blob/master/doc/02_output.md`

[6] Courtesy of `https://maelfabien.github.io/tutorials/open-pose/#run-openpose`

Table 1: Available recording modalities per participant group

Group	Annotation	RGB videos	Kinect	Openpose	Vicon	Nb recordings
3	error label	`avi`, 960x544	`tabular txt`	`dict. txt`	`tabular txt`	540



(a) Kinect (b) OpenPose Coco [6] (c) Vicon

Fig. 3: Pose (Skeleton) output formats of the Kinect, OpenPose and Vicon.

Table 2: Differences with other datasets

Dataset	Activities	Exercises	Nb mvt	Patients	Participant	EMG	RGB-D	MoCap	Nb recordings	Annotations
EMG Squat [7]	Therapy to protect the anterior cruciate ligament (ACL)	Squat	3	0	9	leg	NA	NA	81	Exercise type
EmoPain [2]	Chronic low back pain	Physical exercises	7	22	50	back	multiple-view video & audio	IMU	unk.	pain expression & pain related mvt
HPTE [1]	Physiotherapy exercises at home	Shoulder and knee exercises	8	0	5	NA	Kinect	NA	240	Exercise type
K3Da [6]	Clinically supported motion sequences	Standardised tests	13	0	54	NA	Kinect	NA	525	Exercise type
UI-PRMD [8]	Physical therapy and rehabilitation	Whole-body exercises	10	0	10	NA	Kinect	Vicon	1000	Correct/ Incorrect
TRSp [5]	Post-stroke physical rehab	Arm movements using a haptic robot tabletop	2	9	19	NA	Kinect	NA	190	Error label
LBPPR	Low-back pain physical rehabilitation	Upper-body exercises	3	12	20	NA	Kinect	Vicon (Group3)	2622	Error label + (Group1a,2a: body part, timespan)

10.1145/3154862.3154925. URL https://doi.org/10.1145/3154862.3154925

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