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MPER - a Motion Profiling Experiment and Research system for human body movement

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***Abstract*—State-of-the-art approaches in gait analysis usually rely on one isolated tracking system, generating insufficient data for complex use cases such as sports, rehabilitation, and MedTech. We address the opportunity to comprehensively understand human motion by a novel data model combining several motion-tracking methods. The model aggregates pose estimation by captured videos and EMG and EIT sensor data synchronously to gain insights into muscle activities. Our demonstration with biceps curl and sitting/standing pose generates time-synchronous data and delivers insights into our experiment's usability, advantages, and challenges.**

***Index Terms*—sensor system, smart device, pervasive computing, bioinformatics**

I. Introduction

Motion capturing is essential because it enables the analysis of human gait for several application domains. On the road towards human-in-the-loop computing, more pervasive solutions are needed that correlate motion with its originators to make humans and machines cooperate. One can exploit gait analysis to improve the training and performance of sports athletes. During the summer Olympics of 2020, motion capturing gained special attention, where Intel introduced its 3DAT A.I. to generate 3D models from athletes and extract information like velocity, acceleration, and biomechanics. Increasing computing and virtual storage capacities create opportunities for entirely new approaches to human motion analysis. Indeed a plethora of systems was developed recently. Nevertheless, state-of-the-art solutions do not meet the requirements to generate data for precise motion profiling.

Current gait analysis methods use wearables with sensors, mainly IMU and occasionally floor sensors, for delivering velocity, speed, and orientation data. However, those methods suffer from measurement inaccuracies, mainly derived from a lack of exact data due to an enormous approximation process in IMUs [1]. For supporting the healing process, the rehabilitation domain also tests motion capturing devices, such as DoktorKinnect[1], SilverFit[2], or Corehab Riablo[3]. However, the data quality has been insufficient or even faces severe problems with error rates bigger than 10° when analysing human limbs. The lack of analytical precision using multiple EMG-wearables further reduces the utility of this setup [2].

In the sports domain, requirements go beyond accurately capturing gait and superficially mimicking the appearance of motions. Instead, it requires correlating motion with the performance of individuals. Many sports scientists started questioning the “gold standard” approach, in which current high performers are used as examples for creating training methods, which can increase the risk of injuries and hinder training efficiency. Demand is increasing towards an athlete-centered approach that considers the specific physical prerequisite. For example, exploiting adaptive and smart artificial limbs, is continuously increasing [3]. The approach is supported by the advances in computing in prosthetics. New data models and technical ways of training support seem to be an exciting path for this goal [4]. Nevertheless, technology in sports mainly focuses on measuring quantity (speed, distance, repetitions), not the quality of movements. Due to low data density, current solutions suffer from limitations regarding the accuracy of measurements and oversimplification of data interpretation. Moreover, those systems are not yet capable of motion prediction, as they only capture the motion itself, not why it is happening. Bringing together analytic methods of movement and muscle activity in a time-based context holds potential for a completely new understanding and evaluation of movement quality and also for the support and even regaining of motor skills [5].

We introduce MPER (Motion Profiling Experiment and Research system) to investigate the plausibility of developing a new data model to describe and profile human motion. MPER combines time-series-based tracking of multiple orthogonal motion-capturing systems. Specifically, MPER combines measurements of the muscle and tissue state via Electrical Impedance Tomography (EIT), muscle activation via electromyography (EMG), and the pose of the muscle skeleton via stereo-camera-based motion capturing. Early results indicate the high utility of our approach regarding the meaningfulness of the produced dataset and indicate promising outcomes for further investigation.

[1]https://doctorkinetic.com/
[2]https://silverfit.com/de/
[3]https://www.corehab.it/en/riablo-bf/

II. System Design and Implementation

Our starting point for the data model is various means of measuring human motion and activities. Besides tracking the skeleton pose, we deem it valuable to capture the corresponding muscle activity as well.

The overall system consists of three main building blocks: Wearable, camera, and PC (cmp. Fig. 1). The wearable, incorporating 8-32 electrodes in textile fabric, senses currents and voltages as input modalities and converts them into digital signals. A microcontroller takes care of multiplexing, amplifying, and filtering before relaying this data to the output interfaces. We added USB for wired and Bluetooth LE for wireless connections. While the wearable hard-, firm- and software are self-designed and built, the camera system is developed and used on the NVIDIA Jetson platform. It offers the needed RGB camera-input interfaces and GPU power to perform pose-estimation through machine learning inference. Of the numerous output interfaces provided by Jetson, we use USB and WiFi connections.

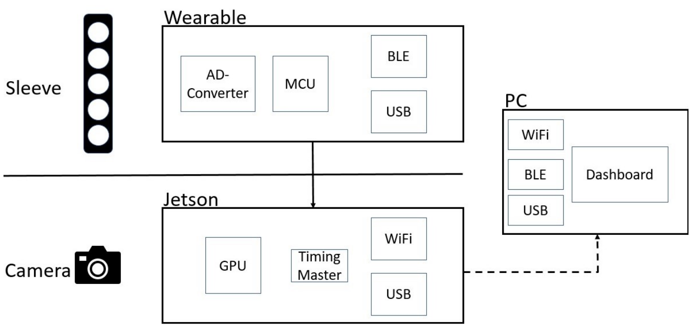

Fig. 1: System Architecture: wearable sleeve with EIT/EMG sensors and camera system on Nvidia Jetson Nano sending collected dato to computing unit

A. Sensor capturing subsystem with EIT, EMG and wearable

1) Electrical Impedance Tomography (EIT): uses electrode measurements on body parts to inferencing electrical conductivity, permittivity, and impedance to generate an image of the internal conductivity. It is, therefore, a non-invasive method of generating a tomographic image. EIT is a relatively safe and low-cost method that generates fast and easily collectible real-time data. EIT can hence be used as a mobile measurement unit for changes in muscle functionality and tissue monitoring. [6] EIT has already shown its clinical use for lung-function imaging, detection of small bleeds in the brain, early detection of breast cancer, gastric emptying detection, and distribution of ventilation among COVID-19-patients [7]. In MPER we use an EIT system that consists of a circuit board and strap with eight electrodes. A circuit board and software are capable of using up to 32 electrodes.

2) Electromyography (EMG): To measure the muscle action potential, we are using EMG. That helps us see when a specific muscle group starts to contract. The technology is widely adopted in medical diagnostics, so we wanted to include it in our data model. Measured activation peaks give additional information, which can improve the analysis of the electrical impedance tomograms. We use two electrodes attached to the skin surface to measure the potential differences between those two. The analog input signal gain gets amplified and filtered to reduce noise while persisting information. The resulting voltage amplitudes concerning time get traced and later visualized.

3) Wearable: To get the necessary analog signals for EIT and EMG, we have to ensure a reliable fixation of the electrodes on the skin. A state-of-the-art approach would have been self-adhesive electrodes. However, this solution introduces several disadvantages. We need at least eight electrodes to monitor one limb. The tomograms also require equal spacing between them to improve the measurements. Placing individual electrodes would take much setup time, and still, the attachment of the electrodes would be very fragile. To conduct field measurements, we needed to develop a more robust and reliable solution that is easy to set up. It also has to scale since we do not only monitor single but multiple limbs. Textile solutions (sleeves) lend themselves to this application for several reasons. Stretching the textile (stretchable woven fabric - 81% PA, 10%PES, 9%EL) yields an even distribution even given different circumferences of, for example, the upper arm. That facilitates simpler re-use with different subjects. The electrodes (stainless steel snap fasteners) are always at the same distance from each other in this case. Furthermore, the electrode and supply line components can directly be integrated into the sleeve, resulting in an easy-to-handle overall system. Another advantage of the design is that the sleeve and its components are washable. That ensures hygiene throughout several measurement set-ups for applications close to the body.

B. Video Capturing Subsystem

We use two stereo 8MP cameras combined with the NVIDIA Jetson Nano for motion capturing. A computer vision algorithm processes each video, and the calculated landmarks get connected and rendered. The generated output consists of pose coordinates and the rendered visual overlay. Regarding the systems "in-the-field"-use case, the pose estimation algorithm is optimized for the low need for computation power and energy consumption. Based on the AlexNet [8] architecture, a regression function is trained to estimate the human pose. The initial stage outputs the coarse body pose within the two-staged CNN, improved by the subsequent refinement stage. The neural network was trained on the LSP and FLIC dataset as the first proof of concept.

C. Data processing and visualization

The third system component is the dashboard application running on a PC. The software for measurement, processing, and visualization is based on the open-source projects pyEIT and OpenEIT. Image reconstruction is achieved with the Jacobian algorithm. The transmitted data of the wearables and camera device gets collected in a JSON file, if needed, processed, and eventually visualized in a data monitoring dashboard. The dashboard itself is a simple python script.

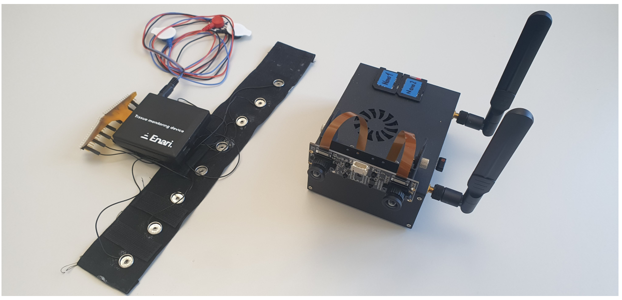

Fig. 2: Demo system - left: EIT/EMG wearable strap with 8 electrodes, right: Nvidia Jetson Nano with dual camera pose estimation

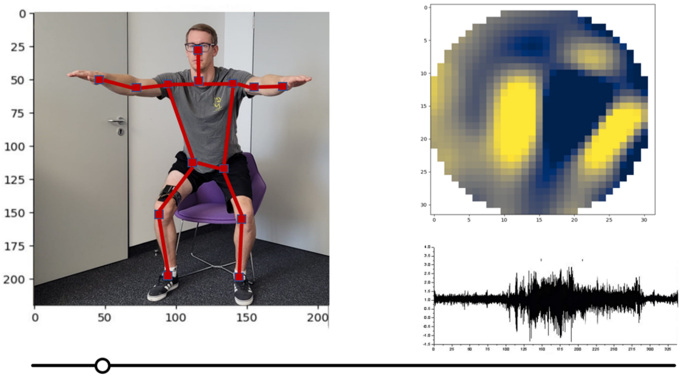

Fig. 3: Dashboard GUI - left: motion capturing after pose estimation, right: EIT muscle profile and EMG muscle activation measurement

It runs a basic GUI built with tkinter and reads in a JSON trace file. A scroll bar is used to navigate the data points corresponding to the timestamp. EIT and EMG graphs are generated using matplotlib.

III. Demonstration

Our MPER demo originates from several experiments and consists of two steps (cmp. Fig. 2. Step 1 uses the wearable to capture the muscle activity and the camera system to generate the pose estimation and store the traces. Step 2 post-processes these traces: we generate graphs and visualize them for analysis inside a desktop dashboard (cmp. Fig. 3). The wearable device gets attached to one of the limbs of the volunteer corresponding to one of the two experiments currently at hand. The camera is positioned so that the whole body is in the field of view of the camera. The volunteer then performs the following two motions:

1) Motion 1 (Biceps curl): We attach the wearable to one of the upper arms of the volunteer. The volunteer performs a biceps curl with a resistance band. During this action, multiple muscle groups are doing their work. The traces will show the flexion of the biceps and extension of the triceps.

2) Motion 2 (Sitting/getting up from a chair): We attach the wearable to one of the upper legs of the volunteer. The volunteer sits on a chair, relaxes, and then stands up abruptly. This fast change of overall posture aims to depict the deltas between the resting and performing muscles parallel to the activation curves.

The data captured by the devices get collected and stored within Jetson. The currently implemented EIT image reconstruction algorithms generate tomograms at a rate of 2FPS for real-time monitoring. In order to enable more continuous time series analysis, the traced data is post-processed and gets replayed in the dashboard application. Pose-estimation (video), muscle activation graphs (EMG), and tomograms (EIT) show data-related correlations between muscle activity and the resulting skeleton movement in a timely context. We visualize the different working muscle groups of experiment 1 and the peaking muscle activation of experiment 2, such as in Fig. 3. Especially the compound EMG and EIT data provides more substantial insights on the interplay of whole muscle groups than EMG measurements alone. The wearable and its integrated electrodes provide an adjustable measurement environment as well.

IV. Conclusion

MPER demonstrates the ability to collect and combine various movement data into a shared, temporal data model. That enables an accurate description of human motion without limitations to any specific measurement method. The vast amount of fast and easy data to capture opens up extensive opportunities for various machine learning approaches and generates comprehensive novel insights. Despite the early stage of development of the system, the insights gathered in our first trials are very promising. Unbound by lab environments, the system's mobility can apply to outdoor activities.

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