Demo: Towards Dynamic Self-Organizing Wearables for Head and Neck Digital Rehabilitation

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ABSTRACT

Digital rehabilitation is dramatically changing the way in which physiotherapists conduct their practice and analyse the exercises of patients. As opposed to traditional treatment with episodic verification of the therapist, patients can perform prescribed exercises at home supported by personalised assistive technologies and wearable devices. This work presents a prototype that highlights the integration of motion data streams from wearable sensors in the context of head and neck rehabilitation exercises. The system consists of self-organising devices placed in shoulders, neck, and head, set up following low-code interaction flows. Patients can interact with the platform through a tablet App that provides feedback through real-time 3D avatars and tracks data for post-exercise analytics.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in ubiquitous and mobile computing**; • **Theory of computation → Semantics and reasoning**.

KEYWORDS

Edge computing, Digital rehabilitation, IoT, Semantics, eHealth

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1 INTRODUCTION

Physiotherapy aids individuals to (re)gain physical functions, range of motion, and improve overall well-being through targeted interventions and exercises [11]. In particular, chronic conditions and surgical interventions might require a rigorous physiotherapy and rehabilitation regime, which might entail *home therapies* given by the physiotherapists to the patient [12]. Traditional physiotherapy relies mainly on the expertise and manual skills of therapists. Although effective, such an approach presents limitations, including scalability and data accuracy/collection, leading to a need for more personalization. Physiotherapy research promotes technological integration into conventional practices, promising enhanced outcomes [2]. Recent trends in digital physiotherapy and tele-rehabilitation further advance in the formalisation of observations and data acquisition to improve diagnostics, therapy personalisation, while offering continuous monitoring capabilities [7]. The most adopted technologies comprise (wearable) sensing devices, 3D cameras, and *smart clothes* [2]. Among the algorithms and techniques, it is worth mentioning machine learning [23], runtime (and offline) data processing and analytics algorithms [6], and distributed coordination [21]. Such technologies and techniques leverage data streams [3, 20] that may include inertial information, patients' run-time feedback, and environmental data, among others. The data variety in these streams presents significant challenges, often mitigated through machine-readable semantic data models such as ontologies and knowledge graphs (e.g., RDF streams [18]). However, current distributed sensing systems still do not provide real-time guarantees [4] nor seamless semantic-based orchestration and dynamics [9]. This study targets the latter challenge, proposing a multi-joint tele-rehabilitation system[1]. It leverages a semantic-based dynamically reconfigurable swarm of wearable sensors and an anthropomorphic avatar-based UI guiding the exercise session. The selected physiotherapy scenario is Head-and-Neck (HaN) rehabilitation. Such a scenario has been selected due to its still unmet need for dynamic sensor-based support systems and the broad diversity of possible therapies, which makes it a perfect testbed. Ultimately, this study highlights two key outcomes: (a) semantic-based sensor swarm formation can improve practices in digital physiotherapy, and (b) a distributed sensor network with synchronised connections that can detect node failures and replace them on-the-fly with minimal disturbance.

The remainder of the paper is organised as follows. Section 2 briefly overviews the state of the art. Section 3 presents the architecture and system design. Section 4 focuses on the system implementation before concluding in Section 5.

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[1]Demo footage in: https://tinyurl.com/57a4dpv8

2 STATE OF THE ART

Digital rehabilitation systems often rely on camera-based approaches and wearable technology to monitor, assess, and support therapies. Moreover, such systems typically include mobile applications (to manage the exercises) and cloud-based data analysis platforms—mainly used by doctors and therapists [13]. On the one hand, several contributions can be acknowledged for camera-based approaches [2]. For instance, Ye *et al.* [22] propose a framework that blends advanced signal processing and computer vision algorithms to analyse motion from infrared camera data, offering a patient-centric kinematic analysis for individualised therapy monitoring and assessment. On the other hand, concerning wearables, a foundational study by Mathie *et al.* [10] validated the use of accelerometers to assess older adults' daily activities within their homes. Timmermans *et al.* [19] evaluated the feasibility, treatment outcomes, and system usability of a sensor-based, task-oriented arm training system, providing strong evidence that digital rehabilitation can improve motor function. Focusing on HaN therapies, several studies have used sensors with remarkable results [8, 14, 15]. Raya *et al.* [15] presented a sensor-based decision support system that uses wearable inertial motion sensors to measure the cervical range of motion. Pérez-Fernández *et al.* [14] aimed to provide objective measurements for cervical range of motion during injury assessment. Kristjansson *et al.* [8] implemented head motion tracking to monitor spinal rotation of a patient following patterns on a screen.

The use of semantic modelling for patients undergoing some form of physical rehabilitation has shown potential for enhancing patient recovery. Manzo *et al.* [9] explored the challenges and opportunities associated with using semantically rich abstractions to model patient trajectories for osteoarthritis rehabilitation using semantic modelling. Similarly, Subiratz *et al.* [17] defined a framework incorporating semantic logic within the context of upper limb rehabilitation, merging the structures of various indicators, medical ontologies, and time annotations. Another study [3] proposed an agent-based semantic stream system that aims to improve the accuracy and efficiency of physical rehabilitation by providing in-time feedback and personalised exercises.

To the best of our knowledge, there is not a digital rehabilitation system employing semantic information to (i) determine the system actors (*e.g.*, nodes) and their corresponding roles, and (ii) provide semantic runtime templates according to the system actors and the user requirements. By incorporating these concepts, we provide the ability to seamlessly manage a heterogeneous sensor swarm and analyse the provided (contextual) information for a given goal.

3 PROPOSED ARCHITECTURE

The main requirements for the system aiming at tackling the challenges mentioned above within HaN rehabilitation are (i) the dressing phase must be semi-automatic, (ii) the sensor discovery and task/plan-sensors association must be ontology-based, (iii) the patient movements must be detected with high fidelity (single joint and derived values), (iv) data analysis and feedback delivery must be performed at run-time (during the exercise), (v) punctual and aggregated user data must be stored for offline analysis, (vi) The patient must have a UI to select their therapy/exercise and get guidance during the exercise.

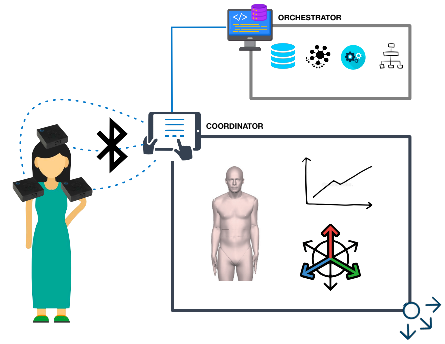

Figure 1: Overall system components.

Figure 1 schematises the proposed architecture to achieve the requirements mentioned above. The system has four key elements: (i) the orchestrator: a back-end node tasked to store patent information (*i.e.*, profile, therapy, and exercises–beyond the scope of this paper) (ii) the coordinator: a master node that manages edge-nodes (*i.e.*, tablet), (iii) edge nodes: leaf nodes of the system that sense or actuate (*i.e.*, sensors, laser pointer), (iv) the semantic Knowledge Graphs: the sensors description, exercises and required capabilities.

The semantics of the underlying concepts characterising HaN digital rehabilitation (*i.e.*, therapy and exercises–neck rotation, strength, flexion movements, shoulder compensation, *etc.*) and the wearable sensing devices characterisation are represented in the form of a Knowledge Graph. Indeed, the sensor nodes can dynamically join the swarm (set of sensing wearables) or be replaced according to their capabilities (*i.e.*, sensing properties, data quality, frequency, connectivity, reliability, and battery level) thanks to a Thing Description (TD) specification[2]. The definition and assignment of the exercises to the patients occur at the *orchestrator* node (beyond the scope of this paper). The *coordinator* node (running on the tablet manages the wearables) identifies the available *edge* nodes (wearables) that match the criteria of a given exercise and allows them to join/form the swarm in charge of the sensing and (if necessary) the environmental monitoring. Once the swarm is complete, the wearable sensors self-calibrate automatically (using the inverted kinematic chain and the free-body movements of the patient), recognising their position—henceforth, their role in the exercise (*e.g.*, head sensors, right/left shoulder). Using the UI (see Figure 3), the patient or the therapist can begin the exercise—thus the data streaming/collection, calculating exercise correctness and deviations, and performance, thus allowing the coordinator node to compute run-time feedback to be displayed to the patient.

4 SYSTEM IMPLEMENTATION

For demonstration purposes, we have implemented a first prototype of the HaN rehabilitation system. It consists of three primary components: (i) wearable sensors for data acquisition, (ii) a tablet for sensor coordination and to display live exercise feedback, and (iii) a server to host and serve patient data and exercise plans.. The implemented functionalities are sensor discovery, connection (and on-the-fly replacement), coordination, data collection, and run-time feedback to the patient through a 3D avatar. The wearable sensors

[2] https://www.w3.org/2019/wot/td

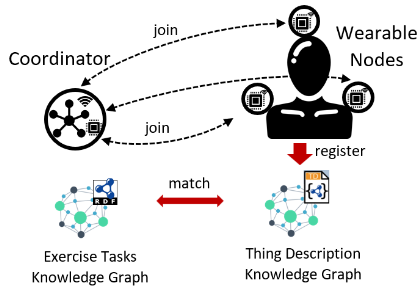

Figure 2: Coordinator node matches wearable nodes according to their capabilities, with the exercise requirements.

are strategically placed (on the head and on the shoulders). The coordinator receives the sensors' data streams in near real-time, processes them, and derives exhaustive information about the head-/neck/shoulders movements and possible compensations.

4.1 Data acquisition and processing

The prototype integrates different technologies in each component (Figure 3). The coordinator node runs on a tablet[3]. As sensing nodes, we have selected the Nordic Thingy:52, a compact multi-sensor development kit designed for IoT applications [16]. The sensor node provides a data stream (at the frequency defined at connection time) containing the values of its sensors. For this use case, we focus on acquiring inertial information (Eulerian angles/quaternions). Communication between the tablet and the Nordic Thingy:52 is over Bluetooth Low Energy (BLE). We leverage a Maximo model [1] to create a realistic 3D representation of the patient and their movement during the exercise. Figure 3 displays one of the interfaces showing the integration of the Nordic Thingy:52 data into the 3D patient model. Moreover, we developed a wrapper for the `Flutter Blue Plus` library with `Thingy52`-specific functionality. The `Thingy52` sensors publish data to the stream every 100 ms. and is comprised of quaternions as a representation of the sensor's orientation.

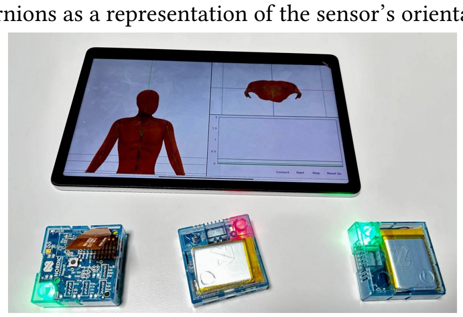

Figure 3: System setup showcasing the sensors and the virtual avatar on the tablet.

The system uses the incremental rotation of sensors over time, enabling us to easily calibrate the system by storing the initial sensor orientation and simply applying the stream of orientations. A quaternion (q) represents the orientation of the sensor and is defined as: $q = w + xi + yj + zk$ where w, x, y, z are real numbers, and i, j, k are the fundamental quaternion units. Let q_t represent the quaternion at time t. The initial orientation is stored as q_0. The incremental rotation of the sensor is calculated by updating the current orientation q_t using the stream of orientations. The resulting orientation is calculated as $q'_t = q_0 {*} x q_t$. Then this rotation is applied to the 3D model directly. For the synchrony of the sensors, we assume a discrete and abstract clock mechanism where each sensor has its own step alongside a system time step. The system clock is equal to the highest time step of the sensors. The time of each sensor is compared to the system clock. Table 1 shows the maximum latency between the sensor timesteps. Accordingly, for this prototype, if a static delay of 10 time steps occurs (possibly due to low battery, connection problems, or hardware errors), the sensor is considered unsynchronized. Therefore, the running exercise is interrupted, and the process of replacing the sensor is triggered.

Time / Sensor	Sensor A	Sensor B	Sensor C
5 minutes	3 ± 0.139	6 ± 0.704	5 ± 0.555
10 minutes	3 ± 0.07	7 ± 1.21	4 ± 0.544
20 minutes	8 ± 1.62	8 ± 1.47	6 ± 0.548

Table 1: Synchronisation steps max latency between sensors

4.2 Semantic capabilities

Semantics enable the creation of abstractions that capture the sensing nodes' essential capabilities, goals, roles, and tasks. These abstractions offer a significant advantage by separating the specific implementation or device functions from the tasks the devices need to perform. This separation improves the discoverability of devices and enhances flexibility, allowing the interoperability of heterogeneous nodes (*i.e.*, from various vendors). Additionally, semantic descriptions of IoT devices allow orchestrator and coordinator nodes to search for or replace them according to their metadata.

The orchestrator *composes* execution plans organising goals and tasks for a given context—*i.e.*, it defines *which* characteristics/specifications are required to be provided by the sensors, *selects* the goal, and *creates* the sequence of actions necessary to achieve such a goal. Such plans are sent to the coordinator. Specifying the node capabilities is crucial for the plan. Indeed, they represent the functional requirements of an application and can be described as skills. The semantic description of these capabilities can be implemented using semantic models for the Web of Things. Specifically, W3C Web of Things, the TD proposes ontology terms for describing affordances. These TD affordances provide machine-understandable metadata about a Thing, indicating the possible interactions consumers can have with it. The TD includes key elements such as metadata descriptions of the Thing, affordances that specify the properties, events, and actions possible with the Thing. Listing 1 shows a JSON-LD snippet representing an event to get the current accelerometer data of Nordic Thingy:52.

```
"events": {
    "accelerometer": {
      "title": "Accelerometer",
      "description": "Get the current accelerometer data",
      "forms": [ {
          "op": [ "subscribeevent" ],
          "href": "uuid:EF680406-9B35-4933-9B10-52FFA9740042" } ]   }  }
```

Listing 1: Nordic Thingy:52 TD - events snippet.

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[3] Xiamo Redmi Pad link: https://www.mi.com/global/redmi-pad

The orchestration and coordination of edge devices require a standardised representation of their key characteristics, such as capabilities, roles, and tasks. Previous works have highlighted the importance of using semantic models to facilitate orchestration. Notably, different ontologies have been developed to address this need, including the Semantic Sensor Network (SSN) ontology and its successor, the Sensor, Observation, Sample, and Actuator (SOSA) ontology [5]. In this demonstrator, we also highlight the importance of representing the tasks using ontology-based representations. In Listing 2 we provide a snippet of a semantic RDF description of an exercise in JSON-LD format, using schema.org vocabulary terms.

```
{ "@context": { "schema": "http://schema.org/", ...  },
  "@id": "http://hevs.ch/exercise1",
  "@type": "schema:PhysicalTherapy",
  "name": "Movement control tests",
  "description": "Active cervical flexion and extension tests",
  "video": "https://www.youtube.com/watch?v=uKjSvHtylUo",
  "bodyLocation": "cervical spine", "procedureType": "Noninvasive",
  "howPerformed": {
    "@id": "http://schema.org/howPerformed",
    "text": "The patient flexes the cervical spine so that the chin moves ..."},
  "schema:exercisePlan": {
    "@type": "ExercisePlan", "schema:repititions": 3,
    "schema:activityDuration": 120, "schema:activityFrequency": 5 },
  "schema:observes":   {
    "@type": "QuantitativeValue",
    "schema:measuredProperty": "oum:Acceleration",
    "schema:marginOfError": "...",  "schema:measurementMethod": "..." }    }
```

Listing 2: Exercise schema.

Following the Web of Things recommendation, we used TD as a semantic entry point for our Thing52 sensors. As shown in Figure 2, the cooridnator needs to match the needs of the task to be executed (*e.g.*, capture accelerometer data for the HaN exercise) with the TD capabilities. To actually connect and acquire the data, semanticTD affordances provide crucial information on how other nodes can interact with them. The orchestration service, to be completed in a next iteration of the prototype, will use this information to identify Things that offer the necessary capabilities for tasks specified in a plan or template. Additionally, the TD specification introduces the concept of a Thing Model, which is a logical description of the potential interactions with a class of Things.

5 DISCUSSION AND FUTURE WORK

This study proposes and tests a prototype leveraging a semantic coordinator and decentralised edge nodes that can join the system (and be replaced) seamlessly. Semantic coordination ensures that the nodes can operate autonomously within the scope and goals of the broader system while maintaining effective interactions and communications. Digital HaN rehabilitation has been chosen as the test bed for the proposed prototype. The complex multi-sensor interactions and the wide variety of exercises allow us to show how decentralised semantics can be applied to edge nodes and support data processing and heterogeneous device coordination. Several aspects of the system are being enhanced to complete all the needed functionalities. Specifically, there is a need to automate the orchestration process to streamline the integration and management of the edge nodes, and incorporate more complex templates that can accommodate different kinds of sensor workflows.

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