D4.8

Proof-of-Concept Testing and Validation in dance, living architectures, sports and entertainment –

Phase 2

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[1] **PU** = Public, **PP** = Restricted to other programme participants (including the Commission Services), **RE** = Restricted to a group specified by the consortium (including the Commission Services), **CO** = Confidential, only for members of the consortium (including the Commission Services).

Table of Contents

Abbreviations

IMS	Individual Motor Signature
GMS	Group Motor Signature
IMU	Inertia Measurement Unit
MoCap	Motion Capture
WP	Work Package

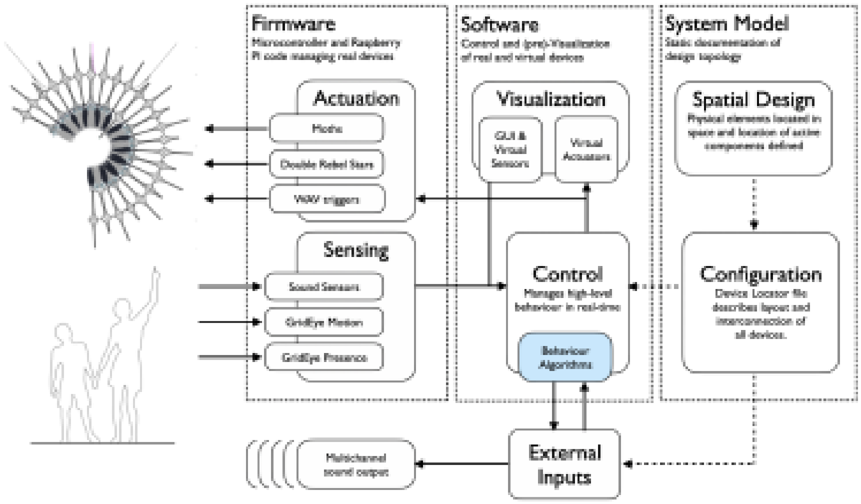
1 Introduction

This deliverable provides an overview of the second stage of development of our proof-of-concept for Scenario 3 in EnTimeMent, where know-how (propagation of mid-level qualities of the movement in the group scenarios) along with the scientific and technological developments from Phase I of the project (WP1, WP2, and WP3) are put to test in out of typical laboratory framework, diving into naturalistic events in ecological settings. The theme of this Scenario is Dance Improvisation as an example of ecologically valid context for research and development of WP2, divided into three stages (Phases).

Initially, we proposed to include in the scenario the possibility of dancers interacting in real-time with non-anthropomorphic dancing partners. The main goal of Scenario 3 is to be able to capture movement qualities in multimodal environments operating at different temporal scales: from milliseconds for electromyographic activity, to seconds for MoCap to minutes for breathing, in expressive motion sequences in which subtle changes in mid-level emotional qualities (e.g., hesitation, aggressivity) or leadership (leading, following) are introduced by the dancers. Further, this scenario includes the possible manipulation through movement sonification, visual coupling, and mobile scenery to enhance the richness of improvisation performance as well as to reveal movement qualities across their different temporal scales, at individual level (IMS, see deliverable D1.3 for detailed description) and at the level of the group (GMS, see deliverable D1.3 for detailed description). The objective is to exploit and test results obtained in the research (see D1.6 for a detailed description), in the automated analysis of relevant individual and social performance qualities along with similarity and dissimilarity measures. The scenario was originally set out to be implemented in collaboration with dance institutions in collaborative Art & Science projects involving dancers, choreographers, and other stakeholders. However, due to the persistent impact of the COVID-19 pandemic on permission to run group scenarios, both in the lab and in more naturalistic environments, some of those plans were adapted. The work with dancers was designed to nourish exploitation of group scenarios in other areas, such as sport, fitness/wellness, cultural wellbeing, and entertainment market areas, explored during the second iteration of the project. Herein, we present our developments in the dance context, in the sport context (dyadic ball exchange and solo long-distance running), and in cultural welfare. The latter consists of the exploitation of EnTimeMent results in the project DanzArTe-Emotional Wellbeing Technology, a novel protocol and interactive system for the interactive embodied experiences of visual art and sonification displays for older people at risk of fragility. The end users in DanzArTe include residents of care homes and museum visitors. This work is based on the adoption of art as a source for stimulating cognitive and motor reactivation: through framework of familiar, religious art older people can experience artworks through their own movement and sensory augmentation (movement qualities interactive sonification).

A further activity consists of the collaboration with the artist Philip Beesley from University of Waterloo and collecting information from the living architecture interaction during his Venice Biennale 2021 artistic project installation (see e.g., Figure 1). This direction was explored during this year, but only a feasibility study was possible due to the persistent pandemic situation.


(a)



(b)

Figure 1: Philip Beesley Living Architectures results from the 12th International Architecture Exhibition, Venice Biennale, 2021 (a). The distributed hardware and software architecture of Living Architecture testbeds (WU) accommodates a variety of behaviour algorithms, coded as 'Influence Engines' which impact the behaviour of physical sculpture components according to their internal logic (b).

2 Improvised group movement scenario – dance context

The goal of the Phase I development was to test the automated analysis of movement qualities and of IMS/GMS propagation in a context of a Dance Improvisation in a group of experts and two novices following the movement of the expert. Their motion capture data was recorded with Qualisys MoCap full-body marker set up (see WP3 and related deliverables on the project platform for more information on the setup in Casa Paganini) and microphone recording their breathing signal captured from the microphone attached to the headsets participants were wearing during the task.

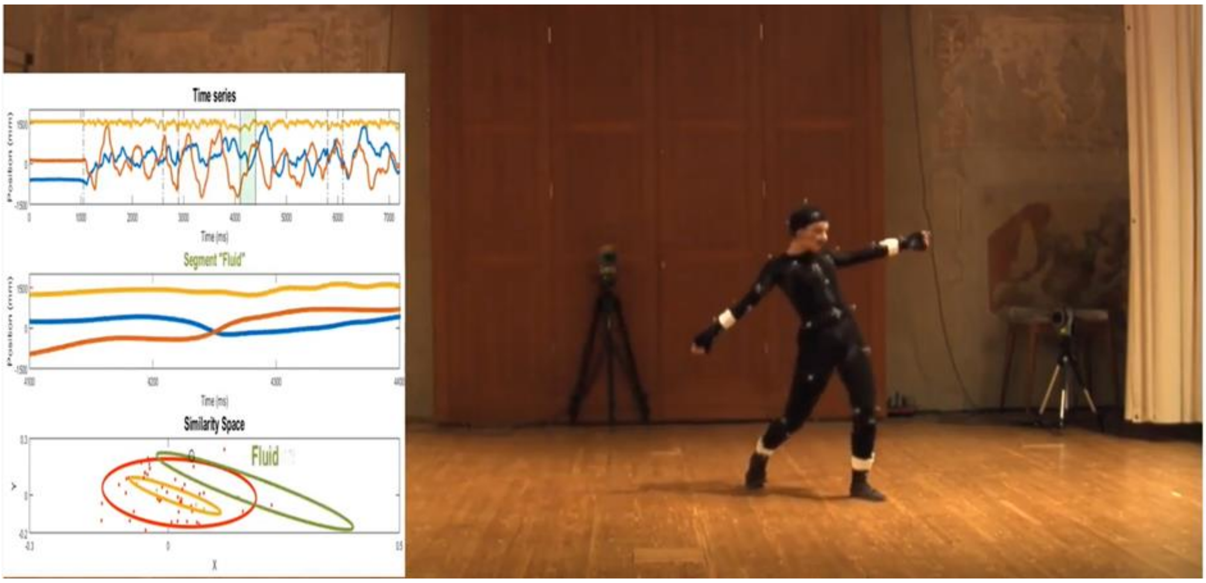


Figure 2: IMS (Individual Motor Signature) differences for mid-layer qualities (ellipses in the bottom panel showing differences in fluid, hesitant and aggressive movement of a dancer) calculated from the pilot recordings with professional dancer Cora Gasparotti recoded for the September EnTimeMent public event “A Tempo!” (http://casapaganini.org/atempo/).

2.1 Warm up routines – one expert dancer with two novices

In January of 2020 in Casa Paganini 14 trials were recorded exploring two warm up exercises led by a professional dancer and two novices (without dancing expertise), all female. All participants were asked to immerse in joint interaction as a part of two exercises.

2.1.1 EXERCISE 1

Instructions: The group of participants (3 or more) are asked to move in space (walking in every direction, even backwards) maintaining a spatial relationship between the members of the group: a metaphor is planets and their satellites. This can be achieved by following or going diametrically in opposition, without however losing the feeling of being bound by a kind of imaginary elastic or gravitational field. Participants are also asked to imagine a "hooking phase" or a kind of common joint breathing, arising when two or more members of the group perceive that they are on the same line, or finding themselves shoulder-to-shoulder and therefore autonomously deciding to move together. It is asked, if in the hooking phase the subjects were hooked but with two different fronts to keep their own face direction and adopt the same direction of movement without changing it: therefore, it may happen that you are forced to walk backwards. Within the group, members must make decisive choices that influence the rest of the group, without hesitation, which allows the person to be the leader of partial part of the group in relation to the rest of the group, of himself in relation to the whole or any other divisions or of the entire group.

Goal: This exercise is very common in dance practice and it is usually used to broaden the group consciousness of a corps de ballet or a course of study. It should enable individuals in a group to perceive others and be perceived even without visual aid. It must also allow all members to be autonomous and be able to make decisions within the group that have an immediate response from the rest of the components leading to the ability of the group to be, without being decided in advance, led by leaders who are always different and equally influential. By repeating this exercise, a cohesive group of autonomous individuals within the relationship should be created and the degree of judgment between individuals should decrease due to the absence of incorrect or correct choices. In fact, there is only the presence of choices that have a consequence that is immediately accepted and implemented by the rest of the group.

2.1.2 EXERCISE 2

Instructions: Participants are asked to move, along a random trajectory, in a formation as unchanged as possible and in turn, in a free and unpredictable way, to propose movement cells to the rest of the group. Each member will then have to acquire the cell, perform it and coordinate with the rest of the group, having the opportunity to change it by proposing a new one or to interrupt it by returning to a neutral walk. The proposals can be rhythmic, sonorous (e.g. vocal expressions, body percussion) and/or movement only, from the danced to the gestural, and can be proposed by each member of the group, not necessarily by a predefined leader or by those who occupy a leading role in the formation (meaning the rows leading the formation, always different depending on the direction chosen by the group independently and randomly). The formation must remain as unchanged as possible allowing each side of the same to be the driving side and therefore often varying leaders as regards the trajectory traveled in space during the duration of the exercise. In some cases, the training maintains the mechanism of the exercise, however, proposing again the satellite effect of Exercise 1, especially if just performed, thus breaking down and reassembling the whole without losing the connection between the components.

Goals: The aim is to stimulate coordination between the members of a group in the most reactive and effective way possible, excluding the premeditation of the leader, whether he is the driving or proponent, of the movements used and the trajectories performed. To stimulate an effective acting, emergence, and exchange of leadership in the group, without the need for a strong direct visual contact, and minimizing or eliminating hesitations in the moments of exchange of leadership.

2.2 Current status and scheduled work

This work is tight collaborative venture between Casa Paganini, EuroMov and those recordings are currently analysed by joint work of the Casa Paganini-InfoMus/UNIGE and EuroMov teams, to extract the mid-level movement qualities emerging from the movement of expert (leader) during Exercise 1 and Exercise 2 – captured as Individual Group Signature (IMS) of leader (expert), and look into propagation of those individual movement features in the novices during unfolding of the interaction – captured as Group Motor Signature (GMS) (expert plus two novices). During the Phase I recordings, no explicit emotional induction took place for the expert dancer nor the novices, therefore only propagation of IMS is sought after in the current framework of analysis delivered by EuroMov (emergence of GMS during the Exercise 1 and Exercise 2). While analysis of this work is still in progress, was recently complemented by a new markerless motion capture campaign (November 2021). In Phase II we collaboratively recorded more groups of three subjects (non dancers), interested in the behavioural cohesion of participants during 10 minutes of recordings, with the groups exposed each to one of three non intrusive soundscapes designed by Casa Paganini-

InfoMus/UNIGE: (I) a neutral soundscape consisting of natural sounds, (ii) a soundscape characterized by a smooth, fluid soundscape inducing positive emotion, (iii) a soundscape designed to induce tension (a Sheperd/Risset raising glissando of a sound texture). The groups, each formed by three participants, were asked to move in space (walking in every direction, including backward and lateral steps) maintaining a triangular, spatial relationship between the members of the group. Participants were also asked to imagine a "hooking phase" or a kind of common joint breathing (instructed to perform upwards “flapping” motion with their arms). Leadership roles were to be exchanged between participants fluently. Participants were prompted to look at the participant they would like to give the leadership to. The duration of the trial was set to 10 minutes, with the assumption this is a sufficient duration to bond the group, and to study the evolution of the cohesion of the group, in terms of the synchronicity of their movements, the fluency of their group behaviour (emergence and consolidation of their Group Motor Signature), heart and respiration.

Figure 3: Participants performing interactive group motion as instructed in Exercise 1 and Exercise 2 at Casa Paganini, led by an expert dancer (Cora Gasparotti).

As a part of feasibility assessment - Phase II (Ethical Approval granted by UNIGE IRB committee) we had run naturalistic recordings of four triads (12 mixed gender, healthy young adults, age M=22.9, SD=1.3), employing markerless MoCap solution. We have combined markerless MoCap with Miqus Hybrid (https://www.qualisys.com/applications/human-biomechanics/markerless-motion-capture/) in November 2021 in Genoa, IT (see Figure 4)

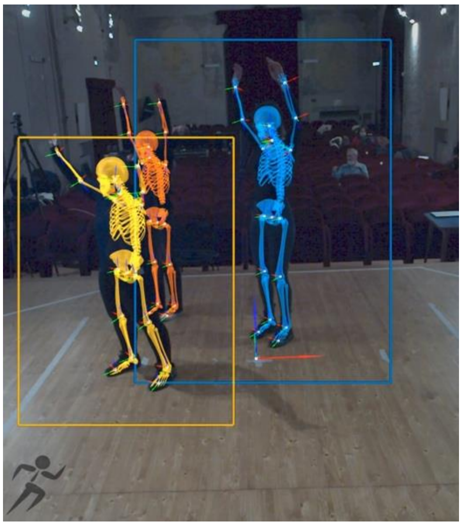


Figure 4: Three participants performing the muti-scale interactive emotionally-triggered group synchronization task during Phase II. The picture illustrates the reconstruction of the three skeletons captured in this naturalistic scenario based on the markerless THEIA analysis.

We also collected respiration information from the audio recordings and Delsys Trigno EKG wireless (https://delsys.com/trigno-ekg-biofeedback/) providing information about the heart rate and heart rate variability that can be aligned at the same time with MoCap (to inform about affective state/arousal of the participants – see example of the ECG analysis run on the Phase II data – Figure 5 and 6).

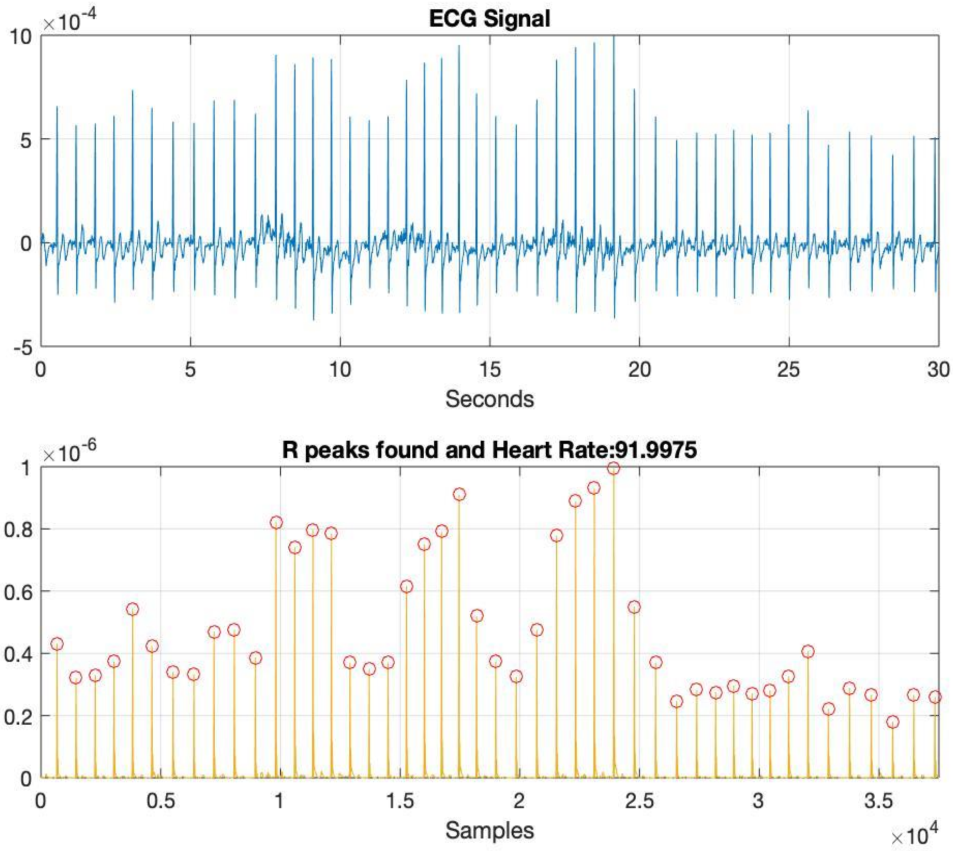
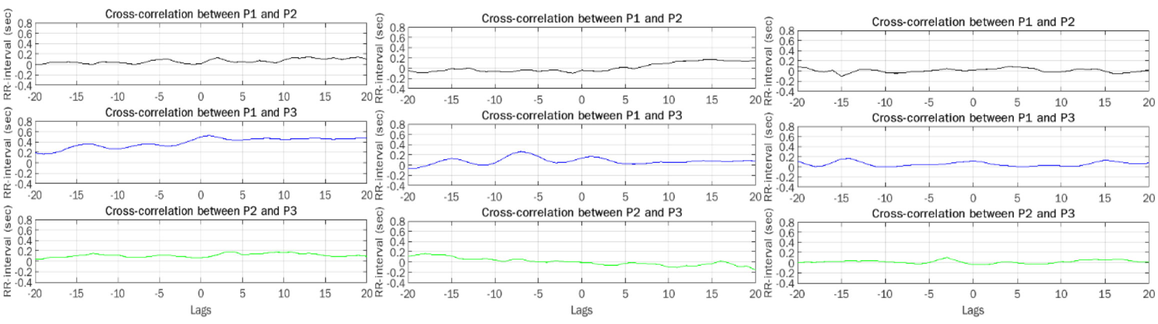


Figure 5: Example of the HR data for one participant during the task

A.



B.

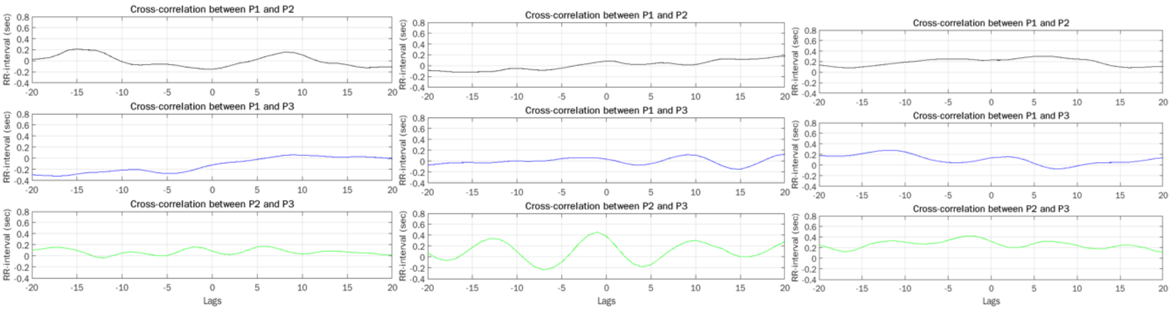


Figure 6: Evolution of cross-correlation of the heart rate in the participants exposed to the calm soundscape (all females group on the top, all males on the bottom).

Participants were instructed with a short video recording describing the purpose of the task, the rules of the task and of communication allowed during the experiment (e.g., no vocal expressions, just exchange with gaze and movement intentions to give or take leadership). One triad has performed the task with the neutral soundscape, two other triads with calm/fluid (positive emotion) soundscape and one other with soundscape inducing tension. All soundscapes were not announced to participants, and were at a very low intensity, in order to obtain a non-intrusive, not explicitly perceived stimulus. Post recordings – participants were asked by a researcher at Casa Paganini to fill in questionnaires asking for cohesion scores with the group members and sense of leadership during the task. Those will be analysed in combination with the kinematic and physiological data collected. The dataset upon completion of analysis will be available to Consortium to extensive and interdisciplinary analysis.

Further plans for Phase III are data collection at Casa Paginini of 10 groups (ideally of four participants) of dance novices or non dancers performing the Exercise 1 Warm up task. The instruction for the task has been recorded by a professional dancer collaborating with Casa Paganini (Cora Gasparotti). Results from the Phase II feasibility study will fine-tune the protocol of the data recordings for Phase III (whether or not we see blueprint of soundscape on the movement data).

3 Dyadic ball exchange – sport context

Despite the COVID-19 pandemic Casa Paganini-InfoMus in collaboration with EuroMov (remotely) has collected data for the experiment on Origin of Movement D1.2 listed as 2.1.8. *Computational methods to automatically investigate the perception of* *the origin of full-body human movement and its propagation, based on cooperative games on graphs.* Data was collected with Qualisys MoCap sport marker set of people throwing ball between each other with different movement intention (117 trials). We have decided to include this dataset in Scenario 3 for the analysis of propagation of mid-level movement features in a sport context. Two people were set at a fixed distance from each other asked to launch a sport ball between each other using two hands with different instructions given at the onset of the task for each trial. Different trials were recorded for the following conditions - repeated launch-grasp 5 times for each participant (alternating) and launch-receive with both hands (Figure 7 for the depiction of the experimental set up).

- “Neutral launch”: the two participants launch the ball using two hands to a fixed target (they do not interact and do not see each other): this is a preparatory “neutral” action. They are back-to-back and do simultaneous launches in opposite directions. We record two individual actions at the same time to reduce the number of recordings: we separate in the post-processing phase as two individual actions with no interaction.
- “Fair” launch of the ball (positive emotion): the two participants are face-to-face, each standing in her own island, and launch to each other the ball, trying to facilitate the grasp by the other.
- “Anger/aggressivity Vs defensive behaviour”: face-to-face, each standing in her own island, the sender launches the ball to the other with anger/aggressivity, then the same is done by the other. Who launches performs with dominance/anger; who receives has necessarily a defensive behaviour (fear-like).
- “Cheating behaviour”: face-to-face, each standing in her own island, the sender launches the ball to the other trying to reduce the success grasp by cheating actions, then the same is done by the other.

Goals: this study primarily looked on the Origin of Movement and extraction of the different time scales from the MoCap recordings based on the intention expressed by the partners during the condition, synchronisation and anticipatory behaviour between sender-receiver in terms of spatio-temporal alignment, leader-follower dynamics.

Work in Casa Paganini is focused on understanding how Origin of Movement explains the change in mid-level movement qualities, in collaboration with EuroMov.

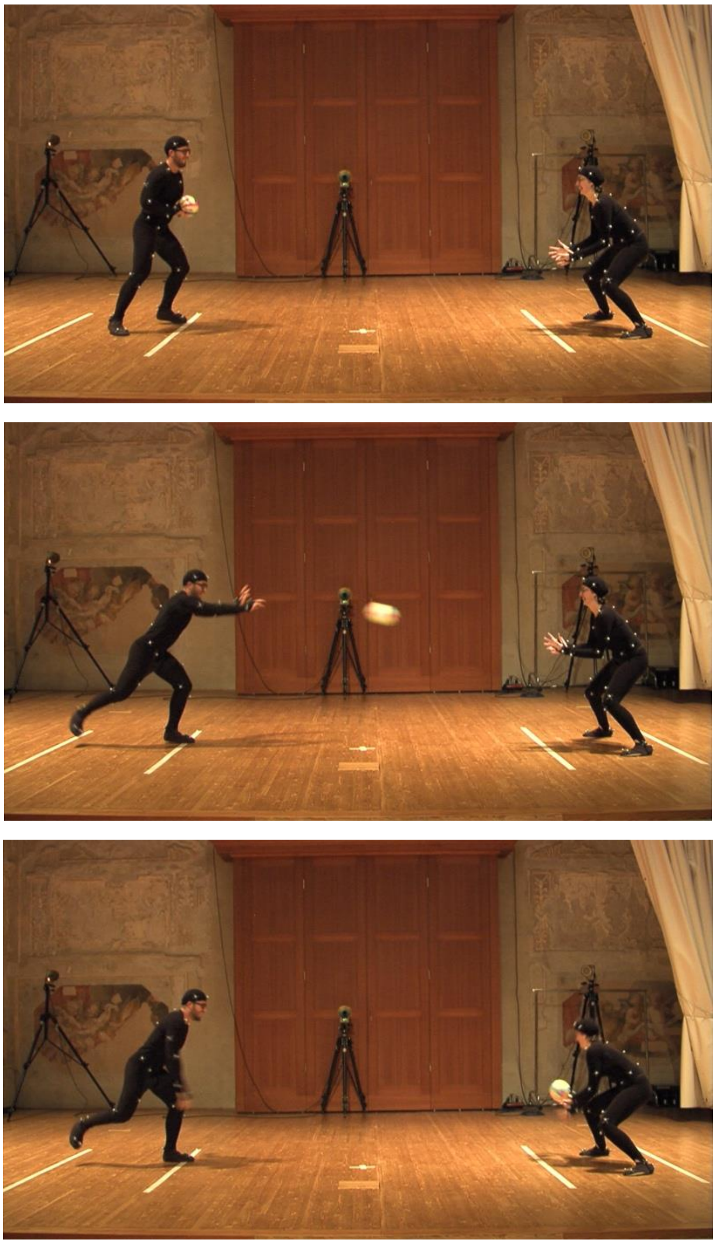


Figure 7: Two participants performing a sport ball pass at Casa Paganini. From the top: preparation, launch, and reception of the ball.

3.1 Current status and scheduled work

The data collection for this project has been finalised and the data is being processed and analysed by cross disciplinary teams of movement and artificial intelligence scientists at Casa Paganini and EuroMov, supported by Qualisys partnership. Current results show significant differences in terms of synchronization between sender-receiver during their interaction, based on the launch conditions and considering mid-level movement features occurring on multiple time scales. These findings support the idea that movement intention and motion qualities affect the way people interact in dyads and how they try to anticipate and respond to their partner's actions. Future work will explore the Origin of Movement (OoM) of both the sender and the receiver, with a particular focus on the time scales at which one perceives the OoM of the partner and the consequent impact on one's OoM. Ongoing work include the analysis based on the interaction design ML integrating and comparing shallow and deep models. Two papers are in preparation on emerging results.

4 Long distance running – solo sport context

As part of the sport context and motivated by the fast-growing market of movement tracking technology to support running and long distance running competitions, we have included long-distance running as one of the use cases of interest in collaboration with UCL and the GDIHub. This work was also supported by a PhD scholarship (Mr Tao Bi, grant awarded by London Legacy Development Corporation (C02955) to the Global Disability Innovation Hub). Full details of the work of the initial studies aimed to develop the scenario is reported in (Bi et al, 2021). We describe here the aim and the initial in-the-wild scenario developed and tested so-far.

A new data collection protocol was developed with the aim to investigate the feasibility to build models that can automatically capture the temporal structures of the experience of running and related runners' emotional and physical states. The aim of this scenario is to support the creation of multimodal dataset related to running to: 1) to evaluate the multi-temporal scale models proposed in in EnTimeMent on non-clinical (clinical in D4.4) in-the-wild datasets; 2) to investigate new methods to gather affective ground truth in the wild in situations where very granular ground truth is necessary, but difficult to acquire. A bespoke wearable voice-based Runner-ESM system (R-ESM) (Figure 8) was developed. It uses multiple sensors (movement related sensors, physiological sensors and voice sensor) and asks voice-based questions every minute during running. The aim is to rethink and redefine ESM (Experience Sampling Method) for ground truth collection for the machine learning algorithms so that it is acceptable by their users in their everyday life (running activity in this scenario) and reliable in contexts where: 1) the ground truth needs to be gathered at very fine temporal definition; 2) the changes in the various affective and physical states of interest may follow very different time scales; and 3) where the relevance of the affective and physical states to model may change across a recording session. We used R-ESM to collect affective and perceive physical state self-reports, physiological and behavioral running data from runners.

Runners of different fitness level are asked to run according to their own running plan while wearing the R-ESM system. While running, they are asked to rate every 1 minute their level of exertion, pain, emotional state and desire to stop. These four states had been selected based on the previous studies on the long distance running and sport psychology literature (Bi et al., 2019). In addition, the runners are invited to think aloud while running to provide more insights about those states or other thoughts they may come to their mind. At the end of their running session, they are interviewed about the feasibility of self-reporting about the experience of running as such high frequency. The collection of think-aloud data, beyond the self-reports) aims to provide more in depth understanding of the dynamic of thoughts during such journey and the level of rich ground truth that could be captured to better modeled the aimed states. Participants are also invited to take part in multiple running sessions if they want. The aim is to further understand how the R-ESM system would be accepted by runners across multiple sessions as the long-term goal could be to build large dataset through crowdsourcing data from people’s everyday run.

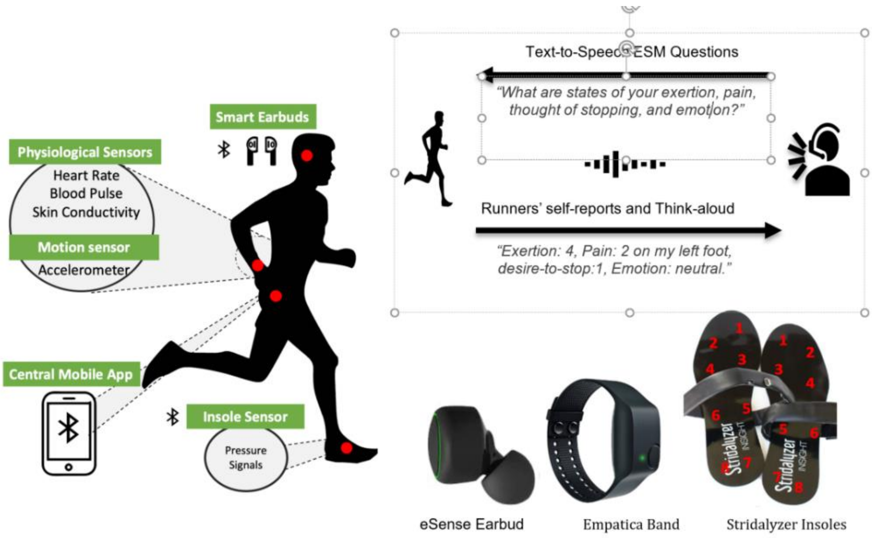


Figure 8: R-ESM: Bespoke system: consisting in pressure sensors, head and arm movement sensors, physiological sensors.

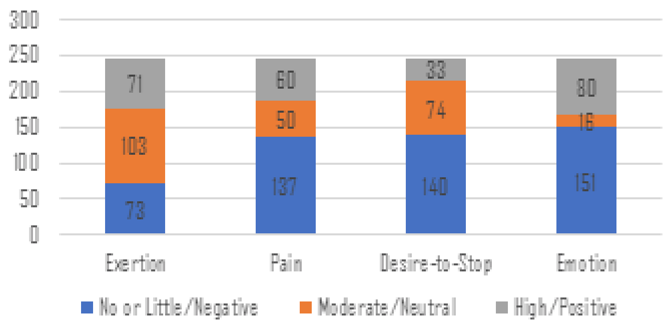


Figure 9: Distribution of self-reported affective and physical state labels collected during running in relation to the sensed data

Table 1: Initial classification results (F1 scores) for the 4 affective and physical states using Random Forest algorithm. (Number in brackets after the F1 scores indicate the number of instances for that level). L=Left, R=Right, HR=Heart Rate; EDA= Electrodermal Activity, BVP=Blood Volume Pulse, ACC=Acceleration, eSense: earbug measuring head movement.

EXERTION	**No/Little (F1)**	**Moderate (F1)**	**High (F1)**	**Number of Instances**	**Weighted Avg. F1**	**Accuracy %**

insole L + R	0.76 (96)	0.72 (127)	0.7 (85)	308	0.73	0.73
HR+EDA+BVP+TEMP+ACC	0.73 (73)	0.74 (103)	0.71 (71)	247	0.73	0.73
Insole L&R + HR+EDA+BVP+TEMP+ACC	**0.83** (73)	**0.78** (103)	**0.75** (71)	247	**0.79**	**0.79**
eSense （Head movement)	0.62 (83)	0.66 (119)	0.55 (78)	280	0.62	0.62
All sensors	0.65 (31)	0.76 (59)	0.69 (34)	124	0.71	0.72
PAIN	**No/Little (F1)**	**Moderate (F1)**	**High (F1)**	**Number of Instances**	**Weighted Avg. F1**	**Accuracy %**
insole L + R	0.86 (163)	0.66 (68)	0.78 (77)	308	0.78	0.79
HR+EDA+BVP+TEMP+ACC	0.86 (137)	0.61 (50)	0.76 (60)	247	0.78	0.79
Insole L&R + HR+EDA+BVP+TEMP+ACC	**0.89** (137)	**0.73** (50)	**0.81** (60)	247	**0.84**	**0.84**
eSense （Head movement)	0.76 (149)	0.59 (56)	0.64 (75)	280	0.69	0.69
All sensors	0.86 (51)	0.78 (28)	0.87 (45)	124	0.85	0.85
DESIRE-TO-STOP	**No/Little (F1)**	**Moderate (F1)**	**High (F1)**	**Number of Instances**	**Weighted Avg. F1**	**Accuracy %**
insole L + R	0.84 (171)	0.72 (98)	**0.5** (39)	308	**0.76**	**0.77**
HR+EDA+BVP+TEMP+ACC	0.87 (140)	0.73 (74)	0.43 (33)	247	0.77	0.79
Insole L&R + HR+EDA+BVP+TEMP+ACC	**0.88** (140)	**0.76** (74)	**0.44** (33)	247	**0.78**	**0.8**
eSense （Head movement)	0.79 (161)	0.55 (81)	0.15 (38)	280	0.63	0.68
All sensors	0.84 (69)	0.73 (44)	0.00 (11)	124	0.73	0.77
EMOTIONAL VALENCE	**No/Little (F1)**	**Moderate (F1)**	**High (F1)**	**Number of Instances**	**Weighted Avg. F1**	**Accuracy %**
insole L + R	0.86 (172)	0.75 (30)	0.76 (106)	308	0.82	0.82
HR+EDA+BVP+TEMP+ACC	0.88 (151)	0.71 (16)	0.75 (80)	247	0.83	0.83
Insole L&R + HR+EDA+BVP+TEMP+ACC	**0.89** (151)	**0.91** (16)	**0.77** (80)	247	**0.85**	**0.85**
eSense （Head movement）	0.83 (157)	0.65 (30)	0.66 (93)	280	0.75	0.76
Alll sensors	0.92 (85)	0.94 (16)	0.68 (23)	124	0.88	0.88

4.1 Initial quantitative and qualitative results

A first data collection has been finalized and initial assessment of the data has been carried out. 11 runners (five males, six females) were recruited for this initial data recording phase for a total 14 running sessions. The duration of running sessions averaged 34.7 ± 15.1 minutes. Eight runners conducted semi-structured interviews, and three participants only had brief informal interviews that lasted for around 5-10 minutes due to participants feeling too tired after running. A total of 384 of self-report requests for the four states were logged and 328 self-reports were collected. We gathered 308 instances of one-minute windows of pressure data from both left and right insoles; and 247 instances of one-minute windows from the Empatica bracelet sensor data (physiological and acceleration signals). 247 instances contained all insoles data, Empatica data and self-reports. Data losses in all sensors and self-reports were caused by Bluetooth connection issues. The distribution of the labelled data is reported in Figure 9.

In this initial analysis of the data, basis statistical features were extracted from each type of sensor and each 1 min window where runner self-reported their states. Each of these windows was centered on the self-report movement. Traditional machine learning analysis were used to assess the level of information carried by each type of sensed data and the possibility to use such type of data to build a runners' affect classifiers. The classification results are reported in Table 1. Only the results with the best performing algorithm (Random Forest) are reported. More analysis of the gathered data using the time-related machine learning architectures are in progress.

In addition to the quantitative analysis, thematic analysis of think aloud and semi-structured interviews revealed that an R-ESM system can be designed to facilitate introspection during running and gather an in-depth description of runners' states. Our interview results show that runners did not find the 1-min spaced questions intrusive and were generally able to answer them. This is an important finding in the context of running. In previous studies, some used a lab-controlled protocol (e.g., leading people to a physiological predefined state of exertion (Buckley et al., 2017), which did not reflect running in the wild. Some used self-report questionnaires only before and after a running session (Guering et al., 2013), which was not sufficiently granular for building machine learning models. Some required runners to stop at regular intervals to fill in a questionnaire breaking the running experience (De Beéck et al., 2018) as well as the validity of the physiological and behavioral data given the repeated imposed rest. One of the reason people did find the process non-intrusive it was because they found utility in it. Participants suggested that such a method could engage runners beyond data collection study sessions by providing them with new opportunities to enhance and facilitate their running posture and strategies. However, they also highlighted how R-ESM systems should be designed for enhancing this outcome. Three main themes emerged that are discussed more in detail in a paper in preparation (Bi et al., 2021): R-ESM could use mindfulness type and style of questioning to make it more natural, relevant and lead to richer and runner's relevant self-reports; R-ESM could take the form of a chatbot rather than a questionnaire to make the gathering state process more of a companion/coach/self-talk -like situations; the focus of the questioning should adapt to the running plan of the day and should vary within it according to a set of factors (exertion level, physical and emotional demand e.g., interval training may presents period where it is easier to engage in a talk vs period (generally burst) where self-report can be very limited or null. It should be noted however that self-talk in long distance running is not unusual but indeed encouraged as a form of physical and cognitive training and it is often adopted by runners. These results highlighted the importance of tailoring the temporal scale of ground truth acquisition to the physical, emotional and cognitive state of the runner. Such understanding has implication in the design of the R-ESM and of the machine learning architecture as it indicates the need for new ways to tie the varying temporal ground truth to the different temporal scales of the sensed data. We are now refining the development of the R-ESM to better understand these temporal scales of self-report and making the self-talking more natural and useful to the runner.

4.2 Scheduled work

Using the qualitative and quantitative results from this study, the work is progressing in three directions. First of all, the work is now being extended by developing a self-report system that operates at timescales meaningful to the person rather than at predefined intervals or using predefined affective states. The aim of the new reporting system is also to help runner be more aware of their states and body movement to gather richer and reliable self-reports for the machine learning training. A new version of the R-ESM and a qualitative study are currently being designed to this purpose. In this new data collection phase, we consider leveraging movement and physiological sensors people are normally wearing rather than being dependent on our bespoke system. This is mainly motivated by the COVID situation but also by its long-term deployment. Leveraging people sensors, will allow us to understand how the scalability of the system and of the machine learning architecture. Finally, in terms of inclusivity, new pathways are also further explored with UCL and GDIHub on inclusion of datasets of visually impaired people tethering running with sighted partner to understand interpersonal dynamic during naturalistic sport scenario.

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