Towards Personalised Learning of Psychomotor Skills with Data Mining

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ABSTRACT

Data Mining (DM) currently represents a key element for improving the acquisition of knowledge and for providing proper feedback in educational environments. In this field, as well as in others, psychomotor skills represent a unique way to advance in the knowledge of human behaviours. Our research apply in two equally promising, but different domains. On one hand, we would be able to improve the learning of psychomotor skills at educational level with the use of different DM techniques. This may includes learning martial arts or supporting the acquisition of locomotor abilities. On the other hand, we would like to expand our DM research far beyond the basis of the aforementioned educational field. Thus, we can evaluate other users, such patients, with the aim of improving the re-learning of motor capabilities during recovery processes on rehabilitation, or even to detect cognitive impairments, analysing slight psychomotor alterations at early stages using DM. The latter includes gait analysis, which are currently used for screening, but not so much for predicting purposes. Although our research is still at early stages, we are following the principles set on previous researches, such those included in our intelligent Expertise Level Assessment (iELA) method.

Keywords

Educational Data Mining, Personalised Learning, Psychomotor Skills, Active Ageing and Education

1. INTRODUCTION

In order to properly apply state-of-the-art DM techniques for personalised learning, we have developed the following taxonomy, distinguishing between *mutually-exclusive* and *non-mutually-exclusive* movements [31]. This differentiation is particularly relevant for psychomotor activity analysis, since learners should be modelled according subtle details, which are not often obvious. In the first *mutually-exclusive* group we can find most of the Human Activity Recognition (HAR) systems, which basically use DM and Machine Learning (ML) techniques to analyse human movements, that cannot be executed at the same time (running, walking, sleeping, etc). In our case, it is extremely pertinent to be able to analyse *non-mutually-exclusive* movements, meaning distinguish different behaviours which are similar. This is the case of analysing distinct personal gait registries or matching several gaits gathered from different users or patients. For recognising the specific *non-mutually-exclusive* human movements, we can use inertial sensors, where the information is often collected in form of Time-Series (TS), like the ones depicted in Fig. 1.

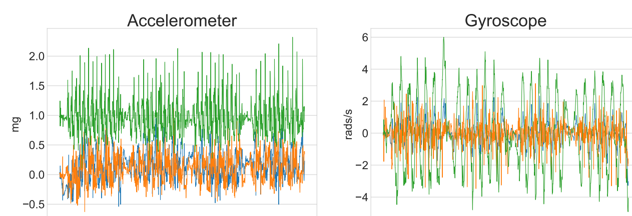

Figure 1: Inertial data recorded representing human activity. On the left side we have the three axis (x, y, z) gathered using an accelerometer. On the right side we have the three axis (x, y, z) gathered using a gyroscope [31].

Fig. 2 depicts another method suitable for breaking down *non-mutually-exclusive* human movements, in this case utilising AI-based video analytics.

Many other different controllers may be used for the purpose of gathering information related to *mutually-exclusive* and *non-mutually-exclusive* human movements, such Microsoft Kinect sensor [29] or LIDAR[1] sensor [20]. Whether the method and sensors used, the aim of the research disclosed on this paper is to analyse, with different DM techniques, several data sets gathered from the execution of human movements, to anticipate psychomotor learning behaviours supporting appropriate feedback or analysis.

This research may also have a specific impact on achieving well-being through active ageing, since the correct execution of certain movements at certain ages allows us to take care

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[1]Acronym of LIght Detection And Ranging.

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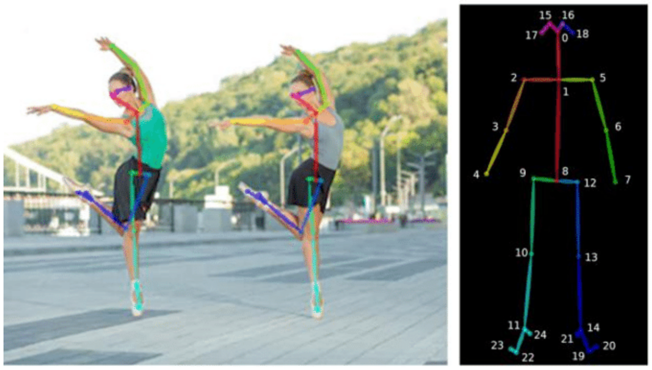

Figure 2: Multi-person Pose Estimation with OpenPose [30].

of ourselves properly. Therefore, the use of DM techniques, which allow us to automatically assess whether we perform certain motor movements correctly or if we preserve certain psychomotor skills, is essential for our comfort and wellbeing.

2. RELATED RESEARCH

The first steps for our research relies on the iELA method disclosed in [31], which uses *quaternions*, a specific group of hyper-complex numbers, to fuse the transformed inertial data, gathered during the practice of different martial arts. iELA uses DM to provide an innovative method to infer performance level, showing its relevance assisting psychomotor learning and educational systems. iELA follows the principles set in [34], which details how the use of different sensors, together with a specific methodology, to support psychomotor learning processes in educational environments. These foundations are also used in [35, 12, 9, 18] since motor tasks can be consolidated into memory through repetitions, creating a long-term neuromuscular memory for specific tasks.

Other intelligent tutoring system related with psychomotor skills can be found in [24], although in this case the authors use physiological sensors. Regarding video analysis, [28] introduce the design, development, deployment and evaluation of video games to support locomotor acquisition in a classroom setting. Other examples are related with the learning of playing piano [8], practising martial arts [33], performing dance step movements [33, 16] or improving sport technique [7], among others.

Some researches, as in [25, 37, 36, 15], use video analysis techniques for human pose estimation, in contrast, iELA foundations analyse inertial data gathered with the use of IMU[2] sensors, as in [22, 32, 13, 5, 21]. iELA analyses the data collected in form of TS, as in [40] but using two different approaches: extracting features, as in [3, 4], and using Convolutional Neural Networks (CNNs), as in [19, 14], taking into account that TS have practically the same topology than images, as mentioned in [6]. Other researches use another DM techniques [23], machine learning methods [26] or neural networks [39, 2, 11].

The use of various methods to estimate accurately the human pose is also common, as in [27, 38, 12] which use two different types of data, the one provided by the IMU and the one gathered from video footage.

In addition to the analysis of psychomotor activities in Educational DM systems, the detection and analysis of the human pose in other research areas, can also take advantage of the different DM techniques described above. Thus, [1] provides automated movement assessment for stroke rehabilitation using video analysis. At this point it is important to denote how pre-dementia stages (motor cognitive risk syndrome) are characterised in some cases by slow gait, as disclosed in [10]. Consequently, this research has an impact on other areas related to psychomotor aspects and, therefore, could also provide tools to promote innovation in active and healthy ageing, increasing healthy life expectancy[3].

3. EXPECTED CONTRIBUTION

In aspects exclusively related to the detection of the human pose in educational environments, in addition to iELA, neither of the examples described above, evaluate the level of performance. As iELA is setting up the principles for evaluating the level of performance of complex movements in martial arts, our aim is to extrapolate iELA to other domains, including educational o health behavioural. The use of *quaternions* to fuse inertial information, with the addition of other sources, such as those provided by video footage, may provide innovative mechanisms on educational and non educational environments that require the analysis of psychomotor skills.

Although one of the desired goals is to merge information coming from different sensors, including video footage, we carefully need to deal with one of the main drawbacks of using a video-based approach for human activity classification purposes, which are the issues in terms of privacy [17]. This will be particularly relevant for fulfilling IDEA (inclusion, diversity, equity, and accessibility) approaches, as well as for satisfying the guidelines for a trustworthy AI, including transparency, explainability, fairness, robustness and the aforementioned privacy.

On this research, we will also consider the analysis of the affective state of the participants within data gathering and in relation to the execution of the movements under our study.

4. RESEARCH QUESTIONS

The affirmative answer to the iELA research question carried out in the Master Thesis [31]:

RQ-1 *Can we use these DM driven analysis (iELA) to automatically classify practitioners according their expertise level?*

represents the starting point for defining the next research question to be carried out in the on going Doctoral Thesis:

RQ-2 *May we use DM approaches to assess the level of expertise accomplished while performing motor activities on*

[2]Acronym of Inertial Measurement Unit

[3]https://ec.europa.eu/social/main.jsp?langId=encatId=1062

different psychomotor learning schemes (from martial arts techniques to physical movements to benefit active ageing) thus achieving a domain transfer?

which will be the main objective of this research.

5. PROPOSED METHODOLOGY

Our proposed methodology is based on iELA, a DM method for an intelligent expertise level assessment which analyses high volumes of inertial data. In this case, when breaking down inertial data, without fusing it into *quaternions*, we cannot clearly distinguish whether the representation corresponds to an expert user, which may be extrapolated to a patient without a pathology, who performs certain motor activity, as depicted in Fig. 3. When fusing this information into *quaternions*, see Fig. 4, we can clearly have information about how the motor activity was performed. On the other hand, if we analyse the same movement executed by a beginner user, which may be also extrapolated to a patient with a pathology, then we can obtain a different depiction, as in Fig. 5.

This approach is based in analysing quality datasets gathered while executing human psychomotor activities. The DM analysis of this data will follows iELA approaches, and may include the use of CNNs and the examination of the extracted features from TS.

6. CONCLUSIONS

Research in the analysis of psychomotor skills represents an important challenge, overall when we are going far beyond the distinction of the *mutually exclusive* movements disclosed alongside this article. At this stage we are looking forward for feedback to support our research with the aim of demonstrating how our iELA method provides a top-notch approach in the treatment and analysis of different psychomotor behaviours on educational, learning or even on health scenarios.

The use of the DM techniques developed in this research may have different fields of application at educational level, but also can be useful for achieving the benefits of active ageing.

7. ACKNOWLEDGMENTS

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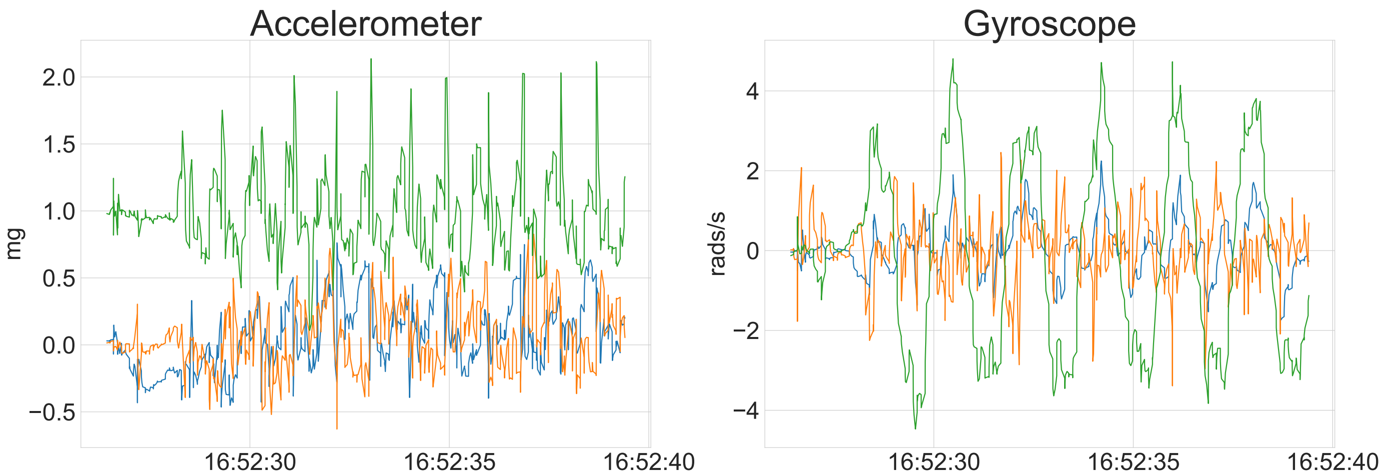

Figure 3: Signals corresponding to the raw inertial data gathered during the execution of a martial art movement in the case of an *expert* practitioner [31].

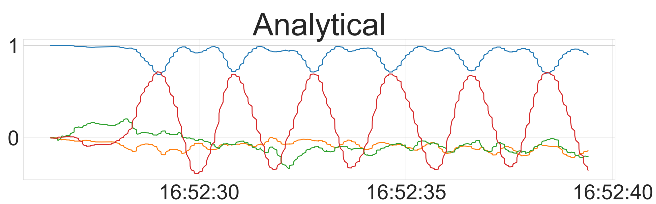

Figure 4: Signals corresponding to *quaternion* fusion obtained during the same movement represented in Fig. 3 and performed by the same user. Analytical means the method used for the *quaternion* fusion [31].

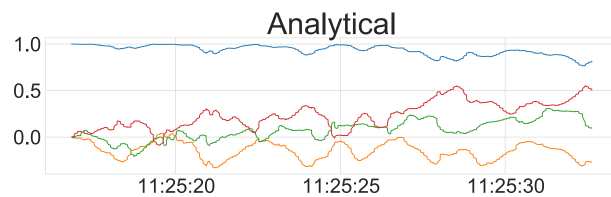

Figure 5: Signals corresponding to *quaternion* fusion obtained during the same movement represented in Fig. 4 but performed by another user. Analytical means the method used for the *quaternion* fusion [31].

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