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ARTIFICIAL INTELLIGENCE IN PSYCHOMOTOR LEARNING: MODELING HUMAN MOTION FROM INERTIAL SENSOR DATA

OLGA C. SANTOS

aDeNu Research Group. Artificial Intelligence Department, Computer Science School. UNED.
Calle Juan del Rosal, 16. Madrid 28040. Spain
ocsantos@dia.uned.es

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Recent trends in educational technology focus on designing systems that can support students while learning complex psychomotor skills, such as those required when practicing *sports and martial arts, dancing or playing a musical instrument*. In this context, artificial intelligence can be key to personalize the development of these psychomotor skills by enabling the provision of effective feedback when the instructor is not present, or scaling up to a larger pool of students the feedback that an instructor would typically provide one-on-one. This paper presents the modeling of human motion gathered with inertial sensors aimed to offer a personalized support to students when learning complex psychomotor skills. In particular, when comparing learner data with those of an expert during the psychomotor learning process, artificial intelligence algorithms can allow to: i) *recognize specific motion learning unis* and ii) *assess learning performance in a motion unit*. However, it seems that this field is still emerging, since when reviewed systematically, search results hardly included the motion modeling with artificial intelligence techniques of complex human activities measured with inertial sensors.

Keywords: Artificial intelligence, Algorithms, Psychomotor learning, Motion modeling, Inertial sensors, Personalization.

1. Introduction

Learning is a complex activity where different aspects are commonly interwoven. These not only include *cognitive* aspects associated with thought, but also *affective* (e.g. feelings, emotions) and *psychomotor* (e.g. kinesthetic skills, body movement) aspects[1]. A range of Artificial Intelligence (AI) tools and approaches have been integrated into learning systems mostly to personalize learning experiences as it is disseminated in the conference series on 'Artificial Intelligence in Education' (AIED)[a] which is now in its twentieth edition. However, the focus so far has only been put on the first two aspects, similarly to my personal research experience which has evolved from cognitive aspects (e.g., a computer assisted assessment system extended with natural language processing, user modeling, and recommendations based on human computer interaction and data mining techniques[2]) to affective issues (e.g., combining several input sources to improve

[a] https://iaied.org/

affect recognition with machine learning techniques from learners' behavior on diverse domains such as Maths[3] or learning a second language through oral[4] or writing[5] practice). However the psychomotor aspects have hardly been addressed in current research[6], but they are called to be the next disruptive factor in educational technology (as acknowledged by the inclusion of that review[6] in the 25th Anniversary Issue of the International Journal of AIED entitled "*The Next 25 Years: How Advanced Interactive Learning Technologies will Change the World*"[b]). In fact, some efforts have already been done in that direction aimed to develop intelligent tutoring systems for psychomotor tasks[7].

In this context, AI innovations can contribute to develop tools that foster the *learning of psychomotor skill*s by providing –and even extending– human capabilities in some way, such as reasoning, learning, remembering, planning and analyzing. For example, AI techniques can be used to teach people how to play an instrument[8], to provide vibrotactile feedback on their martial arts technique[9], to measure the 'timing' of a dance step and how this could be mapped with experts' movements[10], to improve the sport technique[11], etc. These learning domains have traditionally been less studied compared to other 'mainstream' AI-supported learning domains, such as Math.

As inertial sensors are powerful motion measurement devices and are becoming inexpensive and embedded in many wearable devices[12], it is becoming possible and easier to collect rich and meaningful data about learners' physical activity in terms of kinematic information of the body movements. In addition, inertial sensors overcome the drawbacks of video-based approaches[13,14], which are high sensitivity to light conditions and demanding requirements on equipment and infrastructure. In this way, it can be possible to build *personalized adaptive psychomotor learning systems*[6] where: (1) *inertial sensors* collect information about learners' motion, (2) *algorithms* model the movement performed, (3) *knowledge elicitation* techniques are used to design multi-sensorial feedback and (4) actuators finally deliver the appropriate multisensorial personalized *feedback* to learners in each specific learning situation.

In learning contexts where the psychomotor aspect is the focus, learning commonly involves learners *watching* the expert performing the movements and then *practicing* over and over to master those movements until they resemble more and more to the ones performed by the expert[15]. Thus, developing tools that can support and provide runtime feedback to learners in their psychomotor learning process requires effective modeling techniques that can allow in runtime the comparison between the expert and the learner[13,14], taking into account critical aspects such as individual differences, the level of experience, the evolution of the learner over time, the physical context where the performance is executed, etc. In this sense, bringing AI into the psychomotor learning realm requires effective sense-making capabilities and dynamic modeling of learners' motion to select the appropriate multisensorial intervention when the learner does not execute the movement correctly[16]. Hence, offering this *intelligent behavior adapted to the*

[b] https://link.springer.com/article/10.1007/s40593-016-0109-9

current situation and performance requires effective AI approaches that should follow the four phases identified in the *e-learning life cycle*[17], namely: i) design (adaptation hooks upon which the runtime processing bases its reasoning), ii) publication (management of data to allow users access the learning experience), iii) use (access to the tools that provide the personalized learning experience) and iv) auditing (collects usage data to analyze learning experience).

In this context, this paper provides some insights into how advanced the area of AI-supported psychomotor learning is and discusses *the potential of AI to model the motion of complex human activities from a psychomotor learning perspective using inertial sensors during the use phase of the e-learning life cycle*. The rest of the manuscript is structured as follows. **Section 2** introduces the domain of psychomotor learning, the aspects to be taken into account to define psychomotor objectives and motivates the need for a personalized support. **Section 3** positions the modeling of human motion as a pattern recognition problem from inertial sensor data where AI algorithms can be used to recognize specific motion learning units and assess learning performance in a motion unit. To complement this ad-hoc selection of papers, **Section 4** reports a review of the field, which hardly found a couple of specific works regarding the modeling of complex human motion for psychomotor learning using AI techniques. **Section 5** discusses the works reported in Section 3 and Section 4 in terms of i) the psychomotor objectives covered and ii) the AI processing followed for the motion modeling; and suggests future works to advance the field. Finally, **Section 6** presents the conclusions.

2. Psychomotor learning and personalization

Psychomotor learning involves developing skills that require the integration of mental and muscular activity[18]. More precisely, psychomotor skills involve goal-oriented physical actions or tasks requiring voluntary body and/or limb movements to achieve a specific goal[19]. Learners commonly train by repeating very specific movements until they internalize the best way to perform them effectively without conscious effort[20]. According to Mager[21], in order to *define psychomotor objectives*, the following aspects must be taken into account:

- **target**: what the learner will do,
- **condition**: under what conditions will the performance occur, and
- criterion for **success**: how to assess whether the learner has acquired the skill.

These aspects will be discussed when analyzing the works reviewed in this paper, which are reported in Table 3 in Section 5.

Generally, assessment requires the skill to be performed and observed several times using a ranking scale to score the skill[22]. Performance can be measured in terms of speed, accuracy and stamina (endurance)[23]. Nonetheless, there is usually a tradeoff[24] between short-term performance (related to motivation) and long-term learning (related to permanent changes in behavior). For instance, repeating a motion many times together can make the learner improve the performance at that moment, but retention may be nonexistent in the long-term. According to these authors (i.e., Soderstrom and Bjork)[24], in order to induce learning, it seems better to schedule the practice of short periods over several times, although that may not allow the learner to execute the movement properly in each iteration, but the execution will improve from iteration to iteration.

As also discussed elsewhere[25], existing taxonomies[26-30] agree that mastering psychomotor skills is commonly a gradual process. This process involves consecutive performance levels that can be represented as a simplified series of steps[25] as follows:

1) *Low performance level*, the learner can hardly recognize the movement (this deals with sensory awareness, recognition, involuntary actions, imitation, by memory, following instructions…),
2) Supervision not needed,
3) Fluent execution,
4) Refinement by precision,
5) Strengthen and coordination, and
6) *High performance level*, the learner has internalized the movement (without thinking, sophisticated choreography transfer to other domains, creating new movement patterns, planning for improvement…).

Psychomotor intelligent learning systems can be suitable to support learners move up to higher performance levels, for instance by reducing the level of scaffolding support as learners improve their performance, develop autonomy and need less close supervision. Previous analyses of the literature show that current psychomotor learning systems do not adapt and personalize the response according to the learners' needs[6,31]. More specifically, the works analyzed in those reviews mainly focus on helping the learner in mimicking expert's postures and gestures with optical caption technology or wearable inertial sensors, and provide non-personalized visual feedback about the learners' execution.

In order to provide *personalized support during the use phase of the e-learning life cycle while learners develop psychomotor skills, physical actions* need to be[32]: 1) *monitored* in real time (multimodal *sensing* of movement and context), 2) *compared* with experts (movement *modeling* to identify psychomotor errors), and 3) *corrected* when needed (design interventions and deliver multi-sensorial *feedback* taking advantage of ambient intelligence). Thus, there is a need to understand the current state of automated AI psychomotor support in the three areas noted above (sensing, modeling and feedback) so that it could be possible to identify gaps that future research should focus on. This paper aims to produce some insights to the *modeling of learners' motions when training psychomotor skills using AI techniques on data collected with inertial sensors*.

3. AI for modeling human motion from inertial sensor data

Automatic detection or recognition of body movements is increasingly receiving attention as inertial technology becomes computationally faster and cheaper and allows to gather human motion data[33-35]. The output is a *continuous signal in the time domain* (time series)[36]. Segments to be further processed need to be extracted from the continuous data stream (Section 3.1), the raw data in these segments obtained from the sensors need to be abstracted in terms of relevant features (Section 3.2) and the features obtained are to be used as input for algorithms that model the movements comparing the data obtained from a learner with those of an expert (Section 3.3). At this point, two approaches regarding the modeling of human motion can be proposed: i) to recognize specific motion learning units (Section 3.3.1) and ii) to assess learning performance in a motion unit (Section 3.3.2). Section 5 discusses how each of these steps have been addressed on systems that focus on learning complex psychomotor skills, such as the systems reported in this Section and those found in the review carried out in Section 4.

3.1. *Data segmentation*

In order to provide the multisensorial feedback in real time, the information needs to be extracted from continuous streams of sensor data in a time-series analysis.

According to Keogh et al.[37] (and also reported by Avci et al.[38]), there exist several approaches for data segmentation when processing inertial signals which focus on changing the point of detection to try to identify time intervals when there are significant changes in the signal. These approaches are: 1) sliding window (adds new points until the fit-error for the potential segment is greater than a threshold), 2) top-down (iterative end-point fits, which split the data at the best location), 3) bottom-up (merge adjacent pairs of points until the cost reaches a stopping criteria), and 4) the combined approach proposed by Keogh et al.[37] (sliding window with bottom-up with a two level segmentation procedure). In addition, Zhou et al.[39] introduce another approach, which is to use peak points to trigger the data segmentation process.

Nonetheless, the most common approach seems to be the sliding window[35,37,39], which has an additional advantage: it is an online algorithm, and thus, it is able to process a never-ending stream of inertial data on the fly.

3.2. *Feature preparation*

The raw inertial data collected need to be preprocessed in terms of relevant features that model the behavior to be analyzed. Obtaining useful information in terms of features from the inertial data collected in a given segment can require feature extraction (Section 3.2.1), normalization (Section 3.2.2) and dimensionality reduction (Section 3.2.3).

3.2.1. *Feature extraction*

Feature extraction is to be done on the whole motion segment of interest. The goal is to find the main characteristics of a segment that accurately represent the original inertial data by collecting quantitative measures that allow valid, useful and understandable motion patterns to be compared. The resulting annotated dataset is a vector data that contains cues for distinguishing the movements to be modeled.

Typically, as compiled in many works[35,36,38], these features come from the time or the frequency domain. Avci et al.[38] have produced a wider classification list, as in addition to features in the time and the frequency domain, they also consider the time-frequency domain (Wavelet coefficients), heuristic information (such as signal magnitude area, signal vector magnitude, inter-axis correlation), and domain specific, tailored to the specific applications. Ermes et al.[40] also compute speed from GPS location data and Ghasemzadeh et al.[41] also consider morphological features such as the difference between the maximum amplitude and the mean of a signal segment; peak to peak amplitude of signal segment; start to end value of signal segment; slope, first and second derivative; and value and time of morphological points. Figo et al.[36] include the discrete domain with symbolic string descriptions such as Euclidean-based distances.

3.2.2. *Normalization*

Some works on inertial signal processing of human activities data have reported some kind of normalization in the data.

For instance, Zhou et al.[39] use the ratio feature to calculate the proportion of the feature in a single axis and the norm of the features in the three axes, so that it takes into account the motions performed at different strengths by different users.

Sazonov et al.[42] use maximum values overall subjects and experiments to normalize the data collected.

Finally, Mattmann et al.[43] subtract the mean sensor value from the base posture of each user.

Nonetheless, normalizing the data seems to be currently an AI-processing tasks under-explored in the context of inertial sensor data.

3.2.3. *Dimensionality reduction*

When the number of features is too high (which is typical when the aforementioned time and frequency values are computed when processing inertial signals), computational effort and memory increase. In addition, there are irrelevant features that do not provide useful information for the classification. Dimensionality reduction is therefore required, which can be done with two different approaches:

1) feature selection: select the most discriminative features; and
2) feature transformation: combines original features to obtain a reduced feature space that keeps features which collectively provide good discrimination.

Avci et al.[38] propose Support Vector Machines, k-Means clustering, or Forward-Backward sequential search for feature selection, and Principal Component Analysis, Independent Component Analysis, and Local Discriminant Analysis for feature transformation. Camomilla et al.[11] also suggest unsupervised approaches (usually based on k-means) for cluster analysis in the feature selection process. In addition, Wang et al.[35] have proposed the following methods for feature selection: Factor analysis, Minimum Description Length, the Minimum Redundancy and Maximum Relevance, and Correlation-based Feature Selection. Finally, according to Ermes et al.[40], the performance of each feature by the area under the receiver operator characteristic curve (i.e., ROC curve) can also be evaluated for this purpose.

3.3. *Algorithms for motion modeling*

There exists wide literature on human activity recognition where the goal is to classify the whole movement activity the user is doing, such as walking, jumping, sitting, standing, etc. For that, supervised approaches are used for the classification as discussed elsewhere[11,35,38,]. In particular, these are the algorithms mentioned on those works: 1) Decisions Trees[11,38,39], Random Forests[11,35,], Nearest Neighbor[11,35,38,39], Naïve Bayes[11,35,38,], Support Vector Machines[11,35,38,39], Hidden Markov Models[11,35,38,], Gaussian Mixture Models[35,38,] and Artificial Neural Networks[11,35,38,].

However, none of these works have explicitly focused on how to classify human movements in complex learning domains. In addition, in order to provide a personalized response, a finer grain is required in the motion modeling. It also requires to compare the data obtained from a learner with the data obtained from an expert. Thus, taking as input my own research background in this domain[6,31], I have identified the following two approaches to model learner motion gathered with inertial sensors aimed to offer a personalized support when learning complex psychomotor skills: 1) to recognize specific motion learning units (Section 3.3.1), and 2) to assess learning performance in a motion unit (Section 3.3.2).

3.3.1. *Recognizing specific motion learning units*

Recognizing motion learning units aims to model different postures, actions or gestures in a given activity (time evolving movement) which are to be practiced by the learner till mastery reproducing the experts' execution. These learning units can be used for instance to compute the time spent completing a specific motion and analyze if that time amount is appropriate. In addition, errors can potentially be flagged by comparing learners' motion with experts' since a finer grained analysis could help identifying repeated errors in the movements, which could also guide the learner into a "correct" movement.

For this, a repository of movements can be used to assess the motion performed using some kind of states representation. Typically, Hidden Markov Models (HMM) are used. In HMM the system is modeled as a process with unobserved (hidden) states that are not directly visible, only the output, which is dependent on the state. This technique allows comparing novice's movements with the ideal version using dynamic time warping[44]. Yamato et al.[45] seem to be the first to apply HMM to recognize human action from time-sequential data, following previous work in the area of speech recognition. However, these authors applied this approach only to motion data captured with image processing.

In the music domain, Bevilacqua et al.[46] have used HMMs to compare in real time a performed gesture when conducing an orchestra with a set of prerecorded examples using a real-time warping of the performed gesture to the recorded reference. In particular, each sensor value is associated to a Markov chain state. The multi-dimensional Gaussian model is used as a state observation probability function. The result is real-time alignment (time warping) of the performed gesture to the recorded reference. The comparison can be done with several references simultaneously as it computes the likelihood at each time.

Kwon et al.[15] collected inertial data from sensors on users' wrists when practicing karate kicks and used HMMs to identify particular movements from the motion data. The Simple Euclidean distance metric is used to measure the similarity between motions and the time to complete the task as an overall performance measure. They create a HMM per motion with a two-state machine topology that identifies the start and end of the movement. Baum-Welch method is used to find the local maximum of the probability. The detection process uses the Viterbi algorithm for the probability of the observations. The detected motion is resampled to the resolution of the reference motion in the motion data base to compensate for potential timing differences when comparing the reference and the obtained score value.

Hence, it seems that AI algorithms allow to define different states during the execution of the movement along time and remove the temporal deviations among executions in order to recognize the motion units to be learnt.

3.3.2. *Assessing learning performance in a motion unit*

Modeling a given motion learning unit can be done to assess the learners' performance, for instance in terms of the level of skill acquisition with respect to an expert in the movement. Usually, learners are classified into beginners and advanced in terms of key performance analysis of the technique[11]. In addition, it might also be relevant to analyze if other aspects such as age, gender or way of learning impact on the performance[15].

A couple of works have been found regarding the modeling of the learning performance with AI techniques. Kunze et al.[13] trained a Nearest Neighbor clustering algorithm to differentiate amateurs' Tai-Chi movements from experts' collected with a wearable inertial sensor. Authors found that expert's inertial signals are smoother and more periodical. The same approach was also used to differentiate two specific Tai-Chi movements.

Similarly, the same wearable was used by Heinz et al.[14] to differentiate amateur and experts in Kung Fu. In this case, authors commented that they have used a Decision Tree (C4.5), Nearest Neighbor and Naïve Bayes classifiers, but do not report details.

In this case, AI algorithms can use the classification process to find the features that characterize the performance level of novice learners and experts. In fact, in terms of the inertial signals, the execution seems to be more stable, thus producing signals that are more periodical and smoother.

4. Review of the field

In addition to the works reported and discussed in the previous section, a review of the field has been carried out. For this, some search keywords have been defined to perform the corresponding search. The keyword "artificial intelligence" was fixed in all searches. First the keyword "psychomotor learning" was added, narrowing the search with "inertial sensors" or "accelerometer" when results were over fifty. However, as it is shown next, when analyzing the papers found, they did not present AI research on modeling complex motor tasks. Then, instead of "psychomotor learning" a more generic concept was used, consisting of several combinations of human movement (or motion) modeling (or modelling). In this case, two papers regarding the modeling of complex human motion such as the ones to be trained in psychomotor learning were found.

The databases used for the searches were the following: IEEE Explorer Digital Library[c], ACM Digital Library[d], Science Direct (Elsevier)[e], Springer Link[f] and Google Scholar[g].

In the rest of the section, the results of the searches done are reported. The review was performed in November 2018. In all cases the process was similar. First, the selected keywords were used in the proposed databases. Papers found were compiled in a spreadsheet, indicating the database where they were found. Next, a selection was done based on the title. Those whose title seemed of relevance, were selected for detailed reading. Relevance was evaluated based on the reading and checked if they reported the use of AI techniques to model the performance of complex psychomotor tasks from inertial sensor data.

4.1. *Results from searches with "psychomotor learning"*

Table 1 shows the results obtained when executing the search {"artificial intelligence" "psychomotor learning"} in the selected databases.

Table 1. Results obtained from the search {"artificial intelligence" "psychomotor learning"}

Databases	Results	Relevant
IEEE Xplorer Digital Library	0	0
ACM Digital Library	0	0
Science Direct (Elsevier)	3	0
Springer Link	31 (3 selected for reading)	0
	185 (search narrowed)	
Google Scholar	13 (when narrowed with {+"inertial sensors"})	0
	17 (when narrowed with {+"accelerometer"})	0

It can be seen that zero results were obtained in the IEEE and ACM digital libraries, Science Direct showed 3 results, but none relevant. With Springer Link the number of results increased to 31, still none of them was really relevant, although 3 of them were selected for reading. In the same way, Google Scholar returned 185, so the search was narrowed. When narrowed with the term "inertial sensors", 13 results were obtained, being 10 of them authored by the author of this paper. When narrowed with the term "accelerometer", then from the 17 results obtained 9 were again from the author of this paper. Obviously, works from the author of this paper are considered as non-relevant, since the goal is to identify new papers of interest in the field.

[c] https://ieeexplore.ieee.org/Xplore/home.jsp
[d] https://dl.acm.org/
[e] https://www.sciencedirect.com/
[f] https://link.springer.com/
[g] https://scholar.google.com/

4.2. *Results from searches with “human movement/motion model(l)ing”*

The literature has also been reviewed with 8 different combinations of keywords that include “artificial intelligence”, human movement/motion model(l)ing, and “inertial sensors” or “accelerometer” in the selected databases. In particular, keywords used were:

KW1: {"artificial intelligence" "human movement modelling" "inertial sensors"}
KW2: {"artificial intelligence" "human movement modeling" "inertial sensors"}
KW3: {"artificial intelligence" "human motion modelling" "inertial sensors"}
KW4: {"artificial intelligence" "human motion modeling" "inertial sensors"}
KW5: {"artificial intelligence" "human movement modelling" accelerometer}
KW6: {"artificial intelligence" "human movement modeling" accelerometer}
KW7: {"artificial intelligence" "human motion modelling" accelerometer}
KW8: {"artificial intelligence" "human motion modeling" accelerometer}

Results from each search are counted in Table 2. A total of 60 distinct results were returned (some papers were obtained in several searches), but only 10 of them were selected for reading as they seemed to report research on human motion modeling with inertial sensors.

Table 2. Results obtained from the searches with the 8 combination of keywords in the following databases: IEEE (IEEE Xplorer Digital Library), ACM (ACM Digital Library), Elsevier (Science Direct - Elsevier), Springer (Springer Link), and Google (Google Scholar). TOTAL counts the number of distinct papers obtained in each database for the 8 searches, as well as for the 5 databases together.

Databases	KW1	KW2	KW3	KW4	KW5	KW6	KW7	KW8	TOTAL
IEEE				1		1			2
ACM									0
Elsevier								2	2
Springer			9	9			6	10	13
Google		1	5	13		7	10	27	50
All									60

After reading in detail the 10 papers selected, only 2 of them specifically addressed the modeling of psychomotor tasks with AI.

On the one hand, Gonzalez-Villanueva et al.[47] model a Yoga movement called ‘Sun salutation’ which consists of 12 Yoga poses. They use accelerometers to collect the temporal series of the motion. It focus on recognizing specific motion learning units but instead of defining the states with the HMM algorithm, they use a Fuzzy Finite State Machine to model the temporal evolution and recognize the different poses.

On the other hand, Yamagiwa et al.[48] present a clustering approach to differentiate beginners from experts, which relates to assessing learning performance in a motion unit. They use a single-class SVM to derive the distances from the origin and then output the results to the distance calculation, obtaining a distance matrix that represents the skill distance and visualizing these distances with multi-dimensional scaling. It is applied to 3 sport activities (i.e., running form, ski’s parallel run and bat swing of baseball), although inertial data is only used in the ski's parallel run and bat swing of baseball. In the first case, skiers are asked to glide a slope with a smartphone on their back to measure the acceleration in the X and Y axes. Results shows that experts are more consistent in their movement. In the second case, an accelerometer and a gyroscope are attached to the bottom of a baseball bat. Similarly, results show that experts keep stable the swing performance.

5. Discussion

Research on psychomotor learning modeling with AI techniques from inertial data collected by sensors seems to be scarce. The review carried out and reported in Section 4 only returned two papers which complemented the four works discussed in Section 3.3 which had been identified in previous reviews[6,31]. However, from those works, there seems to be a lot of potential from the AI perspective to model motion of complex human activities. Thus, this section summarizes the modeling approaches using AI and the psychomotor aspects (as defined by Mager[21]) involved in these six works. Table 3 includes the works that recognize specific motion learning units (as discussed in Section 3.3.1), while Table 4 includes the works that assess learning performance in a motion unit (as discussed in Section 3.3.2).

The six works reported in Table 3 and Table 4 have a clear *psychomotor objective* related to the mastery of complex tasks which are completely different from one another: music conduction, Taekwondo punches and blocks, Yoga, Tai-Chi and Kung-Fu sequences, and sport techniques in ski and baseball. Their conditions focus on being able to properly repeat the movement to be learnt. Success criteria consider the performance of the movement in terms of fluidity or explosiveness, the time required or the difference with experts. Regarding the activity recognition process, all of them use accelerometers as inertial sensors to track the movements of the human body. In addition, four of them also use the gyroscope. Thus, the *signals need to be processed with AI techniques as a time series problem*. When reported, the segmentation is done following the sliding window approach. None of the works have normalized the features nor reduced them. In fact, features extracted differ among the different systems and are very few. The works that focus on recognizing specific motion learning units (Table 3) use some kind of state machine to compare the current motion with predefined postures. For this, either HMM or a finite state machine extended with fuzzy logic is proposed. In turn, in those that focus on assessing learning performance in a motion unit (Table 4), the goal is to differentiate novice learners from experts. Decision Tree, Nearest Neighbor, Naïve Bayes and SVM classifiers are used.

Table 3. Research on modeling psychomotor learning to recognize specific motion learning units with AI algorithms on inertial sensor data.

Reference	Inertial sensors used	AI for modeling human motion			Psychomotor aspects		
		Data segmentation	Feature preparation	Algorithm	Target	Condition	Success criteria
Bevilacqua et al.[46]	Accelerometer and gyroscope	Not needed: gestures are obtained independently	None: seem to work with raw sensor values (e.g., acceleration in axis x, y and z)	HMM to compare in real time a performed gesture with a set of prerecorded examples	Music conduction	Listening a sound file	Smoothness and fluidity, without rigid postures nor stiff gestures
Kwon et al.[15]	Accelerometer	Defines de concept of motion chunk, but the approach is similar to the sliding window: compute standard deviation over 10 points of raw signal, if the second standard deviation is above a threshold, assume that motion starts	Pitch and roll angular values in Euler coordinate system. Define posture (static constant values) and gesture (dynamic movements defined by velocity)	HMM to recognize reference motions from segmented motion chunks	Taekwondo motions (punch, outside block, upper block, inside block and down block)	Posture and gesture training	Time to complete task (learn posture and rapid succession in gesture)
Gonzalez-Villanueva et al.[47]	Accelerometer	Not needed, states are explicitly defined from knowledge of the phenomenon	Angle for each of the 5 sensors with respect to the vertical axis (in the spherical coordinate system) and their derivatives	Fuzzy Finite State Machine to model the temporal evolution and recognize poses	Yoga movement (Sun salutation) consisting in 12 sequential poses	Balance between flexion and extension	Duration of poses and stability

Table 4. Research on modeling psychomotor learning to assess learning performance in a motion unit with AI algorithms on inertial sensor data.

Reference	Inertial sensors used	AI for modeling human motion			Psychomotor aspects		
		Data segmentation	Feature preparation	Algorithm	Target	Condition	Success criteria
Kunze et al.[13]	Accelerometer and gyroscope	100 sample sliding window	20 features, only mention the ones used in the classification: 75% percentile, frequency range power on accelerometer axis, root mean squared.	Nearest Neighbor to 1) differentiate expert from amateur, and 2) to classify 2 different movements	Basic Tai-Chi forward and backward movements of the first form	Repeatedly perform movements	Reduce probability of failing
Heinz et al.[14]	Accelerometer and gyroscope	100 sample sliding window	20 features including: absolute value, frequency entropy, frequency range power, median, mean, 75% percentile, standard deviation, variance for each axis, and absolute sum	Decision Tree (C4.5), Nearest Neighbor and Naïve Bayes to cluster novices and experts	Chum Kiu motion sequence in Wing Tsun (a popular form of Kung Fu)	Repeatedly perform movements	Explosiveness of execution
Yamagiwa et al.[49]	Accelerometer and gyroscope	No mentioned	No mentioned	SVM and multi-dimensional scaling visualization is used to identify the difference between the current data and the target skill	Sport techniques: ski's parallel turn and baseball bat swing.	Trainings to acquire the skill	Distance to target skill

The analysis performed in this paper has limitations since it is not deep enough to comment on the strength and weaknesses of each approach and technique. Nonetheless, it serves as an initial contribution to point out that currently there are not many works that apply AI to provide personalized support for psychomotor learning of complex motion skills but AI definitely has a great potential for that and it is expected to see more research in this direction in the near future. In any case, the works reviewed in this paper have provided some insights in the *research directions to follow*. First, inertial information collected from accelerometers and gyroscopes seems valuable. Second, data segmentation has not been explored in detail, but it has a big impact for the real time delivery of multisensorial feedback. Since current works focus on the modeling, they usually assume that the data is already segmented, but that is not the case in a real world scenario where feedback needs to be applied on the fly. Third, feature preparation is also under considered: there is not a real analysis in the papers on the features to be considered and data normalization is not carried out in none of the works. Fourth, the application of AI algorithms has clearly at least two distinct objectives which can lead to different research lines: 1) compare recorded movements with prerecorded references using algorithms that model different states accounting for time variability, such as HMM or finite states machines, and 2) differentiate experts from novices with typical classification algorithms (Decision Trees, Nearest Neighbor, Naïve Bayes and SVM).

In this context, *future work* can go in several directions. Following the above, more work needs to be done in terms of feature extraction and selection. In this sense, martial arts provide an interesting and useful testbed to explore the modeling and personalization in psychomotor learning[31] because they involve the repetition of well-defined, precise and varied movements that can be measured with current sensor technology. The work introduced elsewhere[49] to research on *features preparation* is still on-going and has been extended to model two specific movements in the practice of Aikido martial art, which are knee walking (called 'shikko') and the swings with a wooden sword (called 'bokken') that have been measured in the wild using the accelerometer and gyroscope of a smartphone.

In addition, research needs also to be done in standardizing the *methodologies for labelling data* that can facilitate replicability and scalability of insights. One candidate can be Labanotation as discussed elsewhere[50]. In particular, the Laban Movement Analysis[51,52] can serve to identify body parts that are mobile, human dynamics or effort involved, shapes made and the transformation process from shape to shape and how space is occupied both in stationary and locomotor movement.

There is also need for methodological approaches that can elicit the appropriate *multisensorial intervention* to be delivered when the learner does not execute the movement correctly. Here, the TORMES methodology[53], which has already been used to identify both cognitive-oriented[54] and affective-oriented[55] recommendations, can be considered.

In parallel, a comprehensive *framework* that could serve as a reference to identify the appropriate AI techniques for providing personalized support for complex learning situations that involve the development of psychomotor skills should be developed.

It would also be necessary to research how *emotions* influence the learning and performance of the physical movements during the psychomotor learning process of complex tasks. For this, the four methodological steps identified in the INT^{2}AFF project[h] should be considered in the context of psychomotor learning: 1) gathering affective information, 2) detecting affective states, 3) modeling the affective state, and 4) responding to affect.

In addition, movement modeling can also be applied in *embodied learning*, where movement is used to improve cognitive tasks and focus on the most appropriate movements to reinforce content being learnt[56] or even to support STEAM (Science, Technology, Engineering, Arts and Math) education by making the Physics concept of moment of inertia easier to understand with the practice of Aikido movements[57].

Moreover, research on *physical activity* (increasing overall activity, especially at higher intensity levels) might also contribute valuable insights that can be used for learning[58] including in the long-term[59].

Finally, movement modeling can also be used for improving *proxemics interaction* (i.e., the study of interpersonal and environmental space), in particular, it can be applied to identify the physicality aspects of learning in the classroom, especially for supporting teamwork learning or the impact of physical aspects of learning in the orchestration of the classroom[60]. For instance, current wearable devices combined with AI techniques can generate evidence of physical movements and gestures in the context of collocated teamwork that can be used for reflection during a debrief session.

6. Conclusions

This paper has analyzed existing literature on systems that support learning of complex psychomotor skills, such as those required when learning sports and martial arts techniques, yoga postures or conducting music. The analysis reported here has focused on the AI algorithms used to model learners' movements so they can be supported in a personalized way when learning complex psychomotor skills. Two main approaches have been identified where AI algorithms are needed: 1) *recognizing specific motion learning units*, and 2) *assessing learning performance in a motion unit*. The first case has mainly been addressed using algorithms that can represent motion states (such as HMMs) while removing the temporal information, while for the second, classification algorithms have been applied on labelled data to differentiate performance level. However, *a scarcity of AI techniques for modeling motion in the context of learning has been noted*. However, it is expected that AI research based on inertial sensor data to support the learning of psychomotor complex tasks grows in the near future.

[h] INT^{2}AFF project: INTelligent INTra-subject development approach to improve actions in AFFect-aware adaptive educational systems. Project website at: https://adenu.ia.uned.es/web/en/int2aff.

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