You Are Off The Beat! Is Accelerometer Data Enough for Measuring Dance Rhythm?

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ABSTRACT

Rhythm is the most basic skill for people learning to dance. Beginners need practice but also close coaching and constant feedback. However, in most dance classes teachers often find challenging to provide attention to each student. A possible solution to this problem would be to automate the provision of feedback to students by objectively assessing rhythm from their movement data. But how effective would a fully automated approach be compared to dance experts in evaluating dance performance? We conducted a study aimed at exploring this by 'measuring' dance rhythm from accelerometer data streams and contrasting the algorithm results with expert human judgement. We developed RiMoDe, an algorithm that tracks bodily rhythmic skills, and gathered a dataset that includes 282 independent evaluations made by expert dance teachers on 94 dance exercises performed by 7 dance students. Our findings revealed major gaps between a purely algorithmic approach and how experts evaluate dance rhythm. We identified 6 themes that are important when assessing rhythm. We discuss how these themes should be considered and incorporated into future systems aimed at supporting people learning to dance.

CCS CONCEPTS

• **Human-centered computing → User models**; *Mobile devices*;
• **Applied computing → Computer-assisted instruction**;

KEYWORDS

dance rhythm detection; accelerometer; dance education

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1 INTRODUCTION

In dance education, one of the most important skills for students to learn is rhythm [8, 23]. Rhythm in dance means to synchronise the dancer's body movements with one or more components of the music. Teachers commonly use a wide range of methods and exercises to help people develop the cognitive and motor skills needed in dancing. Results of these methods vary depending on the dance style [6, 9], each teacher's pedagogy [8, 23], and the difficulties that particular students may face. Moreover, dance teachers commonly have to manage large numbers of students and cannot easily monitor each student's individual progress (e.g. in the dance studio or at home). This makes it challenging for teachers to be aware of students' individual needs and to give personalised attention to them [16]. This means not all students may get the same opportunities for learning or the attention and feedback they require.

There is a growing body of work demonstrating the potential of intelligent tutoring systems (ITSs) to support motor learning [25]. An ITS is computer software that provides immediate and personalised instruction or feedback to learners, with little intervention of a human teacher [5]. In the last decade, some work has contributed to the vision of generating ITSs to support learning to dance. For example, Lee et al. [21] proposed algorithms to automatically extract rhythmic information from traces of human movement. Kitsikidis et al. [19] created an application to teach dancing by engaging users in virtual worlds. In the related field of rhythm learning, researchers have used motion trackers to provide feedback to students learning to play piano [14] and percussion [22].

Although the works mentioned above have made important contributions in the areas of computer-supported dance and rhythm learning, not much work has been done in trying to understand a) how automatically generated metrics of rhythm compare with experts' knowledge; b) how to make sense of quantified information related to how a person is moving rhythmically; or c) how automatically generated feedback can be integrated into current learning practices. In this paper, we are interested in unveiling the gaps between automatically generated metrics of rhythm and the experts' understanding of rhythm (a) as a first step towards bridging the gap between low level digital traces and high level constructs that can be meaningful in dance learning and used to provide feedback. The focus of this paper is two-fold: i) to evaluate an algorithmic approach that measures dance rhythm compared with expert human judgement; and ii) identifying the gap still existing between analytics automatically generated from sensor data and experts' evaluation of rhythmic skills.

To achieve the above, we developed RiMoDe (Rhythmic Dance Movement Detector), a system that transforms accelerometer data into digital traces of information that can be used to measure bodily rhythmic movements. We used this system to evaluate dance students practising partner-dance exercises while they were being video recorded. We asked dance teachers to carefully evaluate different episodes of each student's recorded dancing by responding to a structured questionnaire and freely commenting on the student's rhythmic skills. We report on the accuracy of our pure algorithmic approach compared with the overall experts' evaluation. We also discuss the complex evaluation criteria about rhythm used by experts and how they change the rigour of evaluation according to the student's current skill level. In sum, the contribution of this paper is a mixed methods analysis of the the gap that exists between analytics automatically generated from sensor data and experts' evaluation of rhythmic skills.

The rest of the paper is structured as follows. The next section presents foundations of rhythm, dance learning and technological support for dancing. Section 3 describes our technology to track rhythm. Section 4 presents the study and the tools we used to run it. Section 5 presents the results of our study and Section 6 discusses the identified gaps between our algorithmic approach and experts' rationale. Finally, Section 7 concludes the paper with final thoughts and recommendations for future work.

2 BACKGROUND

2.1 Rhythm in Music, Dance and Life

Rhythm can be found in nature, for example, in the cycles of day and night, ocean waves, heart beats, breathing patterns and the gait of animals [11]. Inspired by those, humans started to develop their human-made rhythms using their bodies (clapping, walking) and instruments (drums, sticks) [11]. In music, rhythm is everything pertaining to the duration quality of musical sounds. A similar concept is *tempo*, the rate of speed of a composition or section, as indicated by tempo marks or by metronome. The term *beat* is also critical to musical rhythm and defines the temporal unit of a composition. Rhythm is formed by a sequence of different patterns produced by beats - stresses and/or pulses that are arranged in a musical composition. Dance often builds on these patterns in music to set its rhythm. Some studies have attempted the opposite, making the music follow dance movements [12].

In short, rhythm consists of the time duration of intended bodily movements with stress or accentuation that follows a pattern. In this paper, we will use the definitions from the dance literature to define: *rhythm* as the patterned repetition of the movement of the body in space and time; and *tempo* as the speed of the music [8, 23].

2.2 Rhythm in Dance Learning

Rhythm is usually taught in dance classes inside a broader topic called *musicality* [6, 8]. Musicality is an abstract topic and, for this reason, teachers' approaches to it vary. Overall, it refers to the quality of the dancer's movement and its connection with the various elements of the music (when there is music). Teachers scaffold the development of rhythmic skills using different strategies, sometimes developing (somewhat) standard exercises [6]. A critical aspect of the instruction is the provision of feedback. Teachers may focus on the technique: quality of body position/movement/alignment and face direction; or on the rhythm itself: precision of movements according to time, accent and duration of the movement [6]. Rhythm in dance education involves the development of quite complex psychomotor skills that allow the body to move in synchronicity with particular elements of the music, which is fundamental for higher order forms of dancing expression.

2.3 Technology support for dance and rhythm learning

Emerging sensing technologies are allowing researchers to investigate learning in a wide range of motor learning scenarios [25]. In one of the pioneering studies applying sensors to track rhythm, Lee et al. [21] several accelerometers were attached to participants to model rhythm in human motion. Their method was evaluated using data recorded from users performing various hand movements. In this scenario, the algorithm reported partially inaccurate results. They also tried to detect the rhythm of one professional dancing Cha-cha-chá. The method was useful for identifying some critical features of the movements, such as pattern length, but was not helpful for assessing the dance movement rhythm. Importantly, investigating the correlation between the system's output and the experts' mental model was suggested as future work.

In another study related to rhythm, researchers placed accelerometers on the wrists and waist of students to understand the learning process of playing a samba percussion instrument [22]. They showed the collected data to students with the aim of promoting students' awareness. Students that saw their movement data compared with the instructor's seemed to learn better than students that received just a score as a performance evaluation.

In a more recent paper [2], authors developed a system to support the learning of movement qualities in dance. The system used Inertial Measurement Unit (IMU) sensors to extract features (jerk and kinetic Energy) that were used to evaluate the movements of dancers in terms of Dynamic Symmetry. However, authors did not test the system with students and also suggested the comparison between the system and experts as future work. In a follow up study by the same team [3, 24], authors suggested the creation of a multimodal repository for the analysis of expressive movement qualities in dance. They recorded 90 minutes of four dance experts performing movements with specific characteristics: fluidity, impulsivity, and rigidity. Authors highlighted the importance of studying the expressive quality in dance performance and how technology can support this process. Once more, authors suggested the evaluation and validation of their data recordings by human experts. These previous works suggest the need for comparing the evaluations of rhythm made by algorithmic solutions with those made by experts. Our paper goes beyond this previous work by addressing this gap.

In our own previous work presented in [7], we used smartphone's accelerometers to track students' movements while performing dancing exercises. Our study explored the feasibility of generating automated student-facing visualisations about rhythm skills development. In this work, students were able to see their data via narratives, summaries and visualisations. Although the data representations were considered clear by students, they could not understand how to use them to improve their dancing skills. Results suggested the existence of a gap between the data presented to them and the sense making needed to incorporate the information automatically generated to improve their learning.

The work presented in this paper is aimed at addressing the gap identified in the literature presented above and in our own previous work. More work needs to be done in order to gain understanding about the differences between an algorithmic approach and the teachers' evaluation. This can allow the generation of more robust algorithmic approaches connected with the higher order psychomotor skills that are needed in dancing.

3 DESIGN OF RIMODE

To address the identified gap in literature above, we conducted a study aimed at exploring how measuring dance rhythm using accelerometer data approximates to expert human judgement. For this, we developed and used RiMoDe. RiMoDe converts accelerometer data into information that can be used to measure a dance student's performance. We embedded the algorithm in a smartphone app, so it could be easily scalable and used by several users. We choose the Brazilian partner dance style called Forró as the learning scenario. We followed a similar strategy as in previous research by others [4, 13], by collecting data from experienced participants and also annotating data from less experienced participants. Data from experienced dancers were considered to be the ground truth dataset. In the rest of this section, we describe the technical components needed to implement and operationalise the rhythm detection system RiMoDe.

3.1 The Dance Movement Data

When teachers evaluate their students, they typically need two pieces of evidence: a reference (guide/rubric) and evidence of student's performance [16]. In dance, specifically rhythm learning, this is not different. The teacher uses a song as the reference and the student's body movement as the evidence of performance [8]. Our algorithm also relies on these two elements. The first, the song, is interpreted as the beats per minute (BPM) of the song that is playing while the student performs an exercise. In this study, we use Forró songs that have a quaternary tempo - which means 4 beats per bar. With the BPM information, we can derive other information such as the cycle of the strong beat, in seconds:

$$Strong\ Beat\ Cycle\ (s) = 60 \div (\ BPM \div 4\ ) \tag{1}$$

The second information, the student's movement, is represented by the data obtained from the 3-dimensional accelerometer found in most smartphones. The smartphone's accelerometer API returns, for each request, the amount of acceleration in each one of the axes (x, y, z) measured in m/s^2 (meters per second squared) and a timestamp (current time of the observation) measured in milliseconds. The effect of gravity (9.81 m/s^2) is included in the axis values depending on the smartphone orientation. An example, of what the accelerometer data looks like, is presented in Figure 1. The green broken line represents the raw data collected by the accelerometer and the blue line represents the filtered data. The numbers represent the beat of the song, once the accelerometer data and the song beat are automatically synchronised. The footprints show what the wave means in terms of the expected student movements. The red dots depict the peaks detected, whose relevance will be explained in the following section. More explanation of the graphed data (e.g. the filtering process) will be given in section 3.3.

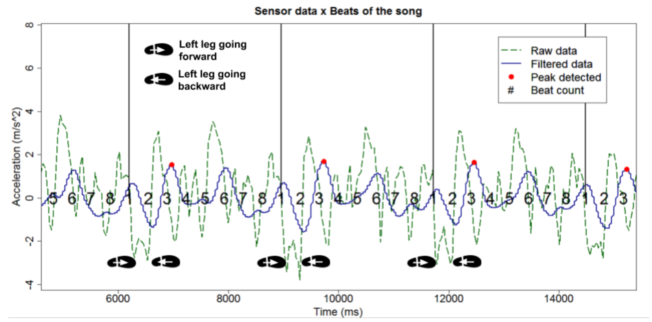

Figure 1: Time series of motion data from a participant while performing a dance exercise. Red dots show peaks detected using our approach.

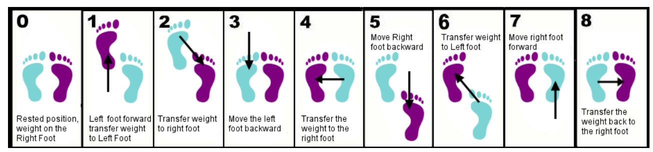

Figure 2: Dance notation for the Básico 1 Forró movement. The purple (darker colour) footprint represents the foot where the weight should be on the corresponding beat of the music.

3.2 Básico 1 movement

The main exercise used for the study reported in this paper is the Básico 1, shown in Figure 2. This is the first basic exercise of Forró that serves to develop many fundamental skills, such as rhythm, balance and coordination. Forró songs have a quaternary tempo (1-4) to which the dancers need to synchronise their steps with. In the Básico 1 exercise, students need to perform a movement in an 8-beat pack: 1) move left foot forward, 2) change weight to right foot, 3) move left foot to the original position, 4) pause, 5) move right foot backward, 6) change weight to left foot, 7) move right foot to the original position, 8) pause. This sequence must be repeated over and over. We chose this exercise because it has a repetitive pattern that is commonly useful for beginner students and thus can easily be automatically detected.

3.3 The RiMoDe Algorithm Description

In this section, we describe in detail how the algorithm RiMoDe works. RiMoDe has two main components:

- RiMoDe_1: converts the accelerometer data into the student's movement rhythm (expressed in Beats Per Minute - BPM) and its consistency (expressed as a percentage);
- RiMoDe_2: uses the output data from RiMoDe_1 and the song BPM to classify if the student's rhythm was the same as the tempo of the song.

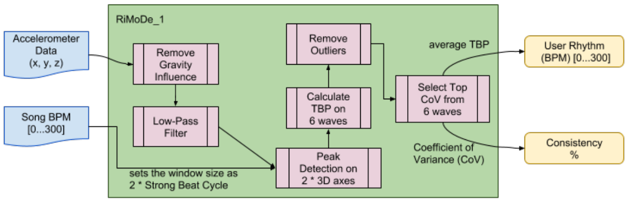

Figure 3: RiMoDe_1. Data flow from the accelerometer, passing through a gravity removal, low-pass filter, peak detection and rhythm calculation.

The first component of the algorithm, RiMoDe_1, is a novel approach for transforming accelerometer data into rhythm information. It differs from previous approaches [e.g. 21] by identifying movement accents and also by using as a reference the beat of the song. The overall solution is shown in Figure 3. The first step is to **remove the gravity** component from all three accelerometer axes, using the formula suggested by the hardware manufacturer[1]. Next, we use a **low-pass filter** to remove the noise enabling a smooth pattern detection and a clear visualisation of the sensor data.

The next step is to **find the peaks** in the wave, that represent accentuated movements in students' motion. We use local maxima as the strategy to find peaks. We use the Song BPM to define the moving windows size of the local maxima algorithm. Even though Forró songs are structured in 4 beats per bar, the Forró dance movements are composed by an 8-beat pack. An 8-beat pack is then defined by 2 times one Strong Beat Cycle which is our window size for finding the peaks. In that way, our peak will be one accentuated movement in each 8-beat cycle. This pattern of one strong accent in a dance movement occurs in several Forró steps. To evaluate our strategy we use a 1-minute session of the Básico 1 step exercise, explained in the previous section.

We calculate the distance between each consecutive peak, that we call "**Time Between Peaks** (TBP)", measured in milliseconds. This feature is commonly used in activity recognition algorithms [13]. The rationale is simple, if the TBP is the same throughout all consecutive peaks and this time distance matches the 2 × Strong Beat Cycle (formula 3), the student is moving in the same rhythm as the song. For each wave, we have a list of TPB occurrences. The last step is to calculate the **Coefficient of Variance** (CoV = standard deviation / mean) for each wave, measured as a percentage. The CoV helps to identify whether the student maintained a regular TBP (or rhythm) throughout the whole 1-minute exercise. We then select the wave that returns the top CoV to represent the student's consistency score. The average TBP of the top wave will give us the student's rhythm, called here User BPM. The average TBP ($\overline{TBP}$) is measured in milliseconds, to translate this value into a more informative measure, we convert it back to BPM, using the formula 4. The value of 1000 in the equation converts the values of TBP from milliseconds to seconds. The value 60 at the beginning of the formula is to convert from seconds to minutes while the 8 (MP, Movement Pattern, formula 2), in the end, converts from user steps to song beats (eight-beat cycle). For example, in a song with 142 BPM, the expected TBP for the student's movement cycle is 3.38 seconds (formula 4 isolating TBP). If the song has a 142 BPM tempo and the student's movements translate to a 135 BPM tempo, the student's movement detected is slower than the song.

[1]https://developer.android.com/guide/topics/sensors/sensors_motion.html#sensors-motion-accel

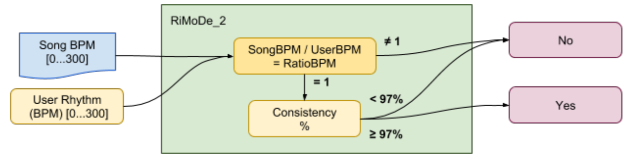

Figure 4: RiMoDe_2. Data flow from the output of the first step (RiMoDe_1) and the thresholds that define good/bad.

$$MP\,(Movement\ Pattern\ Signature\ in\ beats) = 8 \tag{2}$$

$$TBP\ Window\ Size = 2 \times Strong\ Beat\ Cycle \tag{3}$$

$$Student's\ BPM = (60 \div (\overline{TBP} \div 1000)) \times MP \tag{4}$$

The next component of the algorithm, RiMoDe_2, uses the output of the first component to determine whether the student has correct rhythm, or not. Figure 4 shows the decision tree used by this step, with the respective thresholds. The song BPM is compared with the user BPM to result in the Ratio BPM. We only use the song when comparing the overall BPM of the students with the BPM of the song. At this level of analysis, there is no need for real-time synchronization with the raw accelerometer data and the song's beats. The ideal is for the student to have a Ratio BPM close to 1, which means the student has the same BPM as the song used as the reference. The next step of the decision tree is to check the consistency metric. A high consistency means the student kept the rhythm regularly throughout the whole song/exercise.

3.4 Ground Truth

Ground Truth, in machine learning, is a dataset used to test and validate a model [4]. We used the ground truth dataset to validate the results of the annotated dataset to understand what are the expected good values for Ratio BPM and Consistency. The ground truth dataset was gathered by recording the dancing movements of five advanced Forró dancers, performing the Básico 1 exercise. These dancers produced a total of 92 records. The average Ratio BPM was 1.0 (SD = 0.02) and for Consistency they obtained an average of 98.1% (SD = 0.60). We used this Ratio BPM average to calibrate our algorithm's parameters to decide between good and bad outcomes. An interesting observation was that in faster songs the experienced dancers' consistency average dropped to 97.85% (SD = 0.70). For that reason, for the study discussed in this paper (to be presented in Section 5.1), we used the consistency threshold of 97% and the Ratio BPM range between 0.98 and 1.02, when comparing our algorithm approach to the experts' evaluation.

4 STUDY

We recruited 7 participants (4 males, 3 females) from our institution to join a free individual private dance course consisting of 3 classes. Their ages ranged from 18-54, with 5 in the range 25-44. Two participants reported more than 6 years of experience dancing (not professionally), 2 less than one year and 3 no experience at all. Six participants did not dance regularly and just one of the participants had experience with Forró. In each class, the participant was video-recorded individually while performing the Básico 1 exercise a few times, using the app to track and record their movement. Six recordings were obtained per participant in each session, split into two blocks: three before and three after the class. In each block of recordings, the participant was asked to perform the same dance exercise following different songs. A total of 96 videos were recorded. Each participant had at least 6 videos and at most 19, as some participants withdrew in the middle of the study. After the end of the course, we sent the participants' videos to Forró experts to get the students' performance evaluated.

4.1 Video analysis

To evaluate the videos, 6 expert dance teachers were recruited. All of them were professional Forró dance teachers, with more than 10 years of dance experience and at least 5 years teaching dance and/or a higher degree in dance. Three of the experts were male and three were female. Experts annotated the videos remotely using an online video annotation tool, purposely built for this study, without the intervention or observation of the researchers. No further information was used to evaluate our results besides what was obtained during this process. To reduce the evaluation process load for the teacher, each video was assigned to only 3 of them and each teacher evaluated just 48 of the 96 videos. When evaluating a video, the teacher was asked to respond to the following questions: 1) *In this video, does the person have correct rhythm? (Yes / No).* 2) *"Please, include here your comments about the quality of the student's movement. By quality we mean: posture, arms position, legs, feet, joints movement, etc. Be as detailed as possible. Thanks"* The first question allowed us to establish a quantitative common ground for assessment of students' skills across teachers. The second question was intended to elicit qualitative explanations about the assessments.

5 RESULTS

In this section, we explain how we measure the algorithm accuracy. From the 96 videos, two were removed from the evaluation process because the system did not store the sensor data. Since each video was evaluated by 3 different experts, we had cases in which one of the experts disagreed with the other two. For that reason, we created two groups of cases: All Cases, which include the 94 videos; and, Unanimous Cases, which is a subset of All Cases (58 cases) and includes only the videos in which experts made an unanimous decision for the first question.

5.1 The Algorithm versus Dance Teachers

To answer the same binary-answer question as the experts did, the algorithm used only three pieces of information, as explained in Section 3.3.

(1) Song BPM: the BPM of the song, calculated by software, validated by human tagging;
(2) User BPM: the overall rhythm of the student.
(3) Consistency: how much the participant varies their rhythm in the one-minute song/exercise.

We firstly used the Ratio BPM measure to evaluate if the user featured the correct rhythm. Just by using this measure to compare the algorithmic approach with the expert's evaluation, the accuracy reached 79% in the Unanimous Cases (see Table 1a, left).

To improve the algorithm accuracy we added the consistency metric in the decision tree that evaluates rhythm. As some students were in the rhythm during just part of the song, their consistency throughout the one-minute song/exercise was not sufficient to flag them as on the rhythm (Yes). With a threshold of 97% in the consistency metric, the algorithm reached 80% accuracy for the All Cases group (see Table 1a) and 90% accuracy for the Unanimous Cases (see Table 1b).

Table 1: Using Ratio BPM and Consistency. Confusion matrix comparing the experts evaluation (Experts) and the algorithm detection (Predicted) using Ratio BPM and Consistency measures.

(a) All Cases

		Predicted Yes	Predicted No	Total
Experts	Yes	**36**	2	38
	No	17	**39**	56
	Total	53	41	**94**

Precision	68%	Recall	95%
F1 score	79%	Accuracy	80%

(b) Unanimous Cases

		Predicted Yes	Predicted No	Total
Experts	Yes	**20**	0	20
	No	6	**32**	38
	Total	26	32	**58**

Precision	77%	Recall	100%
F1 score	87%	Accuracy	90%

Table 1 illustrates in more detail the confusion matrix and algorithm performance metrics besides accuracy (precision, recall, F1 score). The Precision metric is how correct is the algorithm in identifying True Positives. This is where the algorithm underperformed most. As we can compare with the Unanimous cases, this is where the experts disagree most too. Experts did not have a unanimous decision in 47% (18 of 38) of the correct cases and disagreed in 38% (18 of 56) of the incorrect cases (No). Recall calculates how reliable is the algorithm in identifying all correct cases (Yes). This is where the algorithm performs best, 95% for all cases and 100% in the unanimous subset. The algorithm has a very good performance in avoiding False Negatives. This is quite positive if used in a learning system, as the algorithm has a tendency to overestimate user performance in comparison with the experts. Experts were, in this study, more rigorous than the algorithm. F1 Score computes the harmonic mean between Precision and Recall and is used as a unified metric. For our algorithm performance, the Accuracy is higher than the F1 Score because the algorithm is better at identifying correct (Yes) cases, but this class is under-represented in this dataset.

5.2 What do teachers look for when evaluating rhythm?

An important finding of this study is the set of essential elements that teachers are observing when students dannce to evaluate their rhythm in light of what our algorithm that detects rhythm can or cannot do. Teachers were invited to give comments for each one of the videos they analysed. These comments revealed important

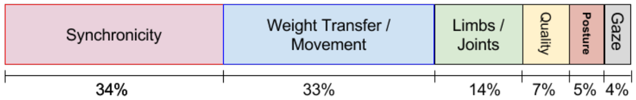

Figure 5: Proportion of the theme's keywords in the experts' comments.

aspects that have the potential to be evaluated using technology. Using a text mining technique called TF-IDF (term frequency–inverse document frequency), which is commonly used to identify how important a word is in a document, we calculated the most frequent terms in the expert's comments and aggregated them according to themes that we found in dance teaching literature [6, 8]. The 6 main themes that emerged from the comments were: synchronicity, weight transfer, limbs-joints, quality of movement, posture and gaze (listed in Table 2). To understand the importance of each theme in the evaluation of rhythm skills, we calculated and ranked the overall proportion of the theme's keywords in all experts' comments (see Figure 5). Regarding the occurrence of each theme in the experts comments, all 6 experts had comments about synchronicity; weight transfer-movement; limbs-joints; and gaze; 5 out of 6 commented on posture; and, 4 out 6 commented on quality of the movements.

As expected, to be in time with the music (synchronicity) is the most important aspect when evaluating rhythm followed by how the student expresses this synchrony using their body (weight transfer/movement). In terms of synchronicity, the following statements by expert 6 represent the kind of comments expressed by all experts when the student in the video was not dancing according to the beat of the music: "*The student has a certain awareness of the rhythm, but still needs to identify it better*" and "*The student was out of rhythm, maybe just a bit but still accelerated, sometimes running over some pauses and waiting on others*". Sometimes, regardless whether the student was dancing with the music or not, experts highlighted problems related to weight transfer. This was expressed, for example, as follows: "*The participant slightly improved the transfer of weight in count 1 but still not enough to say that this is a correct move*" (expert 5); or "*She should take care of weight transfer. Transfer all the weight back and forth, without having to stop the movement*" (expert 1).

The remaining themes are related to the quality of the movement and to aspects that can help to diagnose why the student is making mistakes. For instance, in many cases, experts commented that when the student looks down they spoil their posture and focus the attention on the feet instead of concentrating on the song. In terms of how students should move the limbs, some experts particularly pointed out at problems such as "*lack of relaxation of the joints (ankles, knees, hip, spine) [...] stepping with the whole foot on the floor*" (expert 3) and "*left shoulder being loose while the rest of the joints are locked*" (expert 4). In terms of aesthetical aspects of the movement, experts pointed at certain details that may seem too subtle for an algorithmic approach to capture. For example, one teacher (expert 3) pointed that participant 2 "*was transferring well the weight, but the movement was very mechanical*" and suggested means to correct this problem by "*releasing and relaxing the joints, mainly for the hips*". Consistently, another teacher (expert 2) also highlighted the importance of the "*hip relaxation to help in the execution of the step*". Although posture and gaze, alongside with the quality of the movement, were themes that were not highly commented by the experts, they seem to play a critical role in students quality of dance once the basic rhytmic skills are developed. For example, expert 5 negatively evaluated the technique of one of the students based on his posture as follows: "*he pays attention to postural correction, raising his head and aligning the spine, but cannot stand for more than 5 seconds in the new posture*". By contrast, this same expert also looked at the posture to positively evaluate another student, as follows: "*the posture of the trunk is good and the swing of hip is quite natural*". The importance of gaze was highlighted as an important element that can have a critical impact on posture and, hence, on keeping the rhythm. For example, this was explicitely described by one expert as follows: "*the participant seems to have difficulty maintaining the rhythm in the feet when changes the gaze from the feet to looking forward*" (expert 5). Another expert expressed the kind of feedback she would provide to the students with this problem: "*the participant should avoid looking down to not damage posture*" (expert 6).

Furthermore, the analyses of these 6 themes help us understand another aspect of the expert's evaluation, they tailor their assessments according to student's skill level. RiMoDe treats all participants the same, evaluating each of their sessions separately, without considering previous sessions or students' progress. An expert does it differently. They are able to evaluate more aspects of a student and to adapt their evaluation depending on the student's level. The rigour of the expert also evolves as the student progresses. For example, Participant 6 started the course not being able to stay on the tempo of the songs, but learned the skill and had much better results at the end of the course. Both RiMoDe and experts agreed with the student's rhythm skill progress. Conversely, Participant 4, from the beginning, was able to follow the tempo of the song with high consistency, according to our algorithmic approach, and did not have any improvement. By contrast, experts' evaluation was different. Even though they sometimes agreed that the student was on the tempo, they perceived an improvement of the student throughout the course.

Experts can also shift their focus to more advanced aspects of rhythm once basic aspects are mastered by the students. This is illustrated by the evluation performed by expert 5 assessing the same student at the beginning and by the end of the course. For her first assessment she stated: "*The student did not initiate the dance in the correct tempo of the music, and did not present himself in the rhythm*". After looking at the video of the last class, the expert commented: "*Now, he appears on the tempo throughout the video. The movement is clean and smooth, without bouncing, without twisting the trunk too much, stepping on the tip of his feet with a spring effect, and moving the entire foot to the front*". In sum, an algorithmic aproach to be effective in providing feedback should be able to adapt rigour and adjust the assessments based on the individual's progress across time.

6 DISCUSSION

Our study revealed that despite an algorithmic approach may highly accuratly (quantitatively) identify when a student is out of rhythm,

Table 2: Themes and sample of teachers comments

Theme	Keywords	Details	Comments sample
Synchronicity	rhythm, music, tempo, counting, pause, wait, slow, fast, pace	(Lack of) pause in the movement, too rushed/slow	*Runs over the **pace**, [...], and without **pause time** in the [beat] "3"*
Weight Transfer / Movement	movement, weight, transfer, step, pace, stride, forward, backward	Not transferring, lack of agility, balance	*[...] does not **transfer the weight** well with each **step**, being almost non-existent the second **step**. Work **weight transfer**.*
Limbs / Joints	arms, feet, knees, legs, hips, shoulders, locked, elbows	Joints locked, hips moving too much, twisting	*Homolateral movement with a small **hip** twist [...] that can be harmful in the long run.*
Quality of the movements	mechanical, release, relax, jump	Mechanical, relaxed, jumping	*The movement is very **mechanical**, needs the **release** and **relaxation** of the [...].*
Posture	posture, body, chest, trunk	Position of the feet on the ground, chest should be open	*[The student] needs to improve the **posture**, leaving the **chest** more open [...].*
Gaze	down, looking	Looking down	*Arms locked during dance, **looking down** spoiling [...].*

the experts' assessment of is much richer and complex. The (qualitative) assessments by teachers can be directly articulated as feedback to the students. By contrast, our current algorithmic approach, is limited to identify when students are out of rhythm or if they feature weight transfer problems. In this way, results revealed a need for understanding what is the gap between an algorithmic approach and experts in assessing students' dancing. We suggest that the six identified themes can serve as a basis for scaffolding the design of systems aimed at automating the provision of feedback or the assessment in dance education. Below we summarise the experts' perspectives that emerged in our study; compare these with what can be found in current dance literature; and propose some possible technological solutions to support each theme.

Synchronicity. The Forró experts who participated in our study were concerned about whether the students' rhythm is correct (e.g. it matches the tempo of the song), for how long they stay in the correct rhythm during the exercise, if the student is faster or slower than expected, or if pauses are performed properly. Some of these elements are specific to certain styles of partner dance [26] (like the pause in the fourth beat of the bar for Forró), but being able to dance on the proper tempo of the song is required for all dance styles [6, 8, 23]. The accelerometer sensor was accurate in detecting the tempo aspect of the dancer's rhythm and matching these data with the song. The major difference between the dance experts and technology was the precision and the corresponding degree of flexibility in interpreting movement as 'in rhythm', sometimes adapting their assesments depending on their personal levels of strictness, the skill level of the student and the difficulty of the song. It may be possible for accelerometer-driven algorithmic solutions to measure and predict more complex features of the rhythmic pattern of movement as the teachers do, and to provide user interfaces with user-controlled parameters to vary tolerances for evaluating 'correct' rhythm.

Weight Transfer / Movement. Experts noticed that most of the students' problems were in not transferring their weight at the appropriate time. They also commented that the length of the student's step influences how correct the movement is. In dance, as a whole, transferring weight occurs using many other parts of the body. It requires higher order body control, coordination and balance [23]. In some dance styles, the control of weight goes beyond using the ground, as dancers fight gravity with jumps in the air [8]. The accelerometer can also measure the transfer of weight but to a certain limit. Our approach, using just one 3-axis accelerometer positioned on the hip area, can only detect the movements of the hips and infer some weight transfer information. There is an opportunity to increase the precision and the range of movement being detected by having multiple accelerometers [15] or using other sensors like gyroscopes and pressure sensors [1].

Limbs / Joints. As the main part of the Básico 1 movement occurs in the lower part of the body, teachers were more concerned about the toes, feet, ankle, legs, knees and hips. However, the upper body also plays a key role in dancing [8, 23]. RiMoDe is not able to detect limb or joint movement in this current version, as it is designed to be worn inside the student's pockets. Increasing the number and type of sensors that may be used to model dancing features can contribute in detecting the elements of this theme. For example, it could be possible to include sensors to measure muscular activity, heart beat, skin conductance (e.g. via smartwatches) and breathing [10]. However, there is a trade-off between the number of sensors providing multidimensional data and the feasibility and ease of use by the student.

Quality of the movements. Teachers want the movements to be natural, relaxed and fluid, not mechanical or rigid. Some of the keywords in this theme referred to aspects linked to emotion and energy states, like relaxation and release. In the dance literature, this theme relates to terms like aesthetics, tone, timbre, energy [23], which are widely used in contemporary dance [8]. For this theme, the addition of more sensors will not add much information. A common approach to computationally measuring the quality of movement is the use of Laban Movement Analysis [20] For example, Kikhia et al. [18], described which parts of the body may be most suitable to place accelerometer sensors on to identify the quality of body movements according the Laban Effort Framework.

Posture. Most of the time when experts referred to posture they meant that the student must keep an upright posture with head, trunk and thighs aligned, chest forward and open, normal back curve and abdomen flat. This is particularly important in partner dance where usually the couple is dancing just in front [26]. Even though in one study [15] authors used accelerometer data to detect correct postures of ballet students. Current fabric technology and bending sensors [17] may allow an accurate way to measure the dancer's required posture. One of the challenges with partner dance is the mutual posture of the dancing couple thus a technical solution will also need to take into account the relationship between individual postures.

Gaze. Gaze in the experts' comments of this study were specific to the case when a student looked down to follow their feet. In partner dance, gaze may also refer to the subtle connection that must exist between partners [26]. In this case, head tracking with tilt sensors could provide some information on inferred gaze direction.

7 CONCLUSION AND FUTURE WORK

In this paper we have illustrated the gap that exists between the algorithmic approach to detect rhythm and experts' evaluation in the partner dance education. Experts showed fairly complex interpretation when evaluating students' rhythm. We identified 6 key themes that emerged from teachers' qualitative evaluations that were compared with current research in dance and dance education from a social aspect. Although, our own algorithmic approach (RiMoDe) is limited to assess two of these six themes (namely synchronicity and weight transfer-movement), the study allowed us to identify the trade-offs, potential and limitations of our current technology (based on using a single motion sensor worn close to the hips) in matching what a human observer can identify. Human expertise is a limited resource when it comes to supporting students learning to dance thus a technological approach to feedback provision at scale would be an ideal solution to support both dance teachers and students. This paper should be seen as a first attempt to compare subjective evaluation of human experts with objective measures from a data-intensive solution (materialised as the RiMoDe algorithm). Future work in this line of research will be aimed at considering a richer set of multimodal data streams that can serve to bridge the gap that currently exist between automated dance rhythm assessment and the way experts holistically assess students' performance.

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