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Initial Investigation into Neurophysiological Correlates of Argentine Tango Flow States: a Case Study

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***Abstract*— Argentine tango has been shown to help psychological and physical health by reducing perceived levels of depression and stress, similar and at times better than meditation. An often reported experience in Argentine tango is "flow", which is described as total involvement from the dancers. While this state has been self-reported by experienced dancers while dancing, it has yet to be quantified in real-time. However, with the emergence of portable and wearable devices for the acquisition of physiological signals such as electroencephalography (EEG) and electrocardiography (ECG), and recent innovations in EEG artifact removal algorithms, this quantification may now be possible. In this work presents a case study where we aim to first validate the potential of recording usable EEG and ECG data from dancers while dancing, in an unobtrusive manner, as well as investigate the existence of neurophysiological correlates of Argentine tango flow.**

***Index Terms*— Argentine tango, ECG, EEC, flow, hyperscan.**

I. Introduction

Argentine tango music has been composed by many orchestras during the last century, amounting to a large quantity of music offering a wide stylistic gamut [1]. Argentine tango can be roughly subdivided into three styles: tango, milonga and vals, each suggesting different levels of playfulness and dancing style. While a vals (3/4 beats) can be thought of a smooth ride, a milonga (2/4 beats) sports an underlying playful habanera rhythm often danced in syncopated double time steps by advanced dancers. Dancers improvise along the dance floor using a loosely defined vocabulary of Argentine tango-specific foundational movements allowing dancers to express their personal interpretation of the songs. In recent years, therapies based on Argentine tango have been studied for the improvement of fitness and balance in older adults [2], as therapy for Parkinson disease [3], [4], and depression [5], and as intervention for depression, anxiety, stress, fatigue, and insomnia [6]. Indeed, dancing with a partner to music has more positive emotional effects than without a partner or music [7].

Flow has been defined as "holistic sensation that people feel when they act with total involvement" [8], [9]. It is a mental state in which a person is full immersed in an activity, feeling and performing at their best, colloquially also known as "being in the zone" [10]. This subjective experience has been reported across a wide range of activities, such as sports, learning, dancing, playing music and working. It remains a mystery as to why some individuals report never experiencing it while others report having experienced it multiple times a day [11].

Flow is often linked to moments in the activities when demanding challenges meet a high level of skill. A state akin to flow has been described in dancing [12] and reported by Argentine tango dancers as "tango trance" using qualitative methods [13], [14]. More recently, flow was quantified in Argentine tango dancers as one of several psychological variables associated with the regular and long-term practice of Argentine tango [15]. Using the Short Dispositional Flow Scale (SDFS-2), an abbreviated 9-item version of the long form of the Dispositional Flow Scale-2 [10], the authors found flow to be the strongest predictor of both regular and long-term tango practice [15].

Typically, the assessment of flow relies on questionnaires that are administrated after the experience, event or task [16]. While the assessment of flow could be carried out during the performance of the task, it can interrupt the flow state. To overcome this problem, methods that use physiological signals have gained attention in recent years. For example, [17] presents a viable approach for the use of electromyogram (EMG) and electroencephalogram (EEG) signals to characterize the flow state in sports. The study presented in [18] investigated the correlates between EEG features and a mental arithmetic task designed to evoke flow. The findings in this study suggest the feasibility to discriminate the flow state from other states with EEG features (powers in theta and alpha bands) from the frontal and central area of the scalp. Similarly, [19] studied the effect of skills-demands-compatibility on the emergence of flow with electrocardiogram (ECG) signals and found a reduced heart rate variability (HRV) and increased salivary cortisol levels. They deduced that flow experiences combine subjectively positive elements with physiological elements reflecting mental load and strain.

Additionally, psychological synchrony between individuals emerges in tasks requiring physical and mental coordination. Quantifying such synchrony can help predict task performance, collaboration quality, and learning [20]. Physiological synchrony has been reported in respiration and heart rate signals for choir and surgical teams [21], [22], in electrodermal activity between presenter and audience to quantify the amount of engagement [23], and more recently in EEG for subjects participating in cooperative multi-person

TABLE I

DURATION AND DESCRIPTION OF THE USED ARGENTINE TANGO SONGS.

Song	Duration (s)	Description
S	181	Very rhythmic song
C	161	Very melodic dramatic song
P	205	Melodic and rhythmic music

scenarios [24]. The approach of monitoring multiple people concurrently is known as hyperscanning [25]. Here, synchrony may play a crucial role; as the saying goes "it takes two to (Argentine) tango". As such, to study the synchrony between dancers, physiological signals need to be acquired simultaneously from the lead and follow dancers.

Moreover, multimodal approaches have been used in the fields of brain-computer interfaces [26], [27], quality-of experience [28], [29], and mental workload assessment [30] to provide robustness against movement artifacts. This is true as artifacts rarely affect all the modalities in the same manner, and since different modalities can provide different information about the same physiological phenomenon, increased robustness is achieved. Since movement artifacts are present during dancing, it is unclear if reliable multimodal signals can be acquired in an unobtrusive manner from multiple dancers concurrently. This initial investigation aimed to validate the hypothesis that it was possible to not only measure EEG and ECG signals from dancers under different dancing and no-dancing conditions, but to also assess the impact of dancing motion on the quality of the acquired signals, and ultimately, to find neurophysiological correlates of flow and measures of dancer synchrony. To the best of the authors knowledge, this case study is the first attempt at hyperscanning of Argentine tango dancers under varying flow states.

The remainder of this article is organized as follows: Section II describes the experimental protocol, the devices used for signal acquisition, along with pre-processing, feature extraction, and evaluation methods. In Section III, in turn, the experimental results are presented and discussed. Finally, conclusions are drawn in Section IV.

II. METHODS AND MATERIALS

A. Experimental protocol

Two experienced Argentine tango dancers (co-authors IP and BA) underwent together different experimental conditions while Argentine tango songs were played. In our experiments, three tango songs were used and selected based on their characteristics. These songs were: "S.O.S" (S) by Francisco Canaro (1934), "Cascabelito" (C) by Osvaldo Pugliese (1955), and "Poema" (P) also by Francisco Canaro (1935). The duration and description of the songs are provided in Table I.

The experimental conditions explored in this study were: a) sitting with eyes closed; b) sitting with eyes open; c) dancing in open embrace; d) dancing in close embrace; e) dancing without contact; and f) dancing individually. In all the dancing experimental conditions, BA and IP were the lead and follow dancers, respectively. A total of 15 trials (pairs of condition-song) were performed, as presented in Table II.

TABLE II

LIST OF CONDITION-SONG PAIRS IN THE EXPERIMENTAL PROTOCOL.

	Songs		
Experimental condition	**S**	**C**	**P**
a) Sitting with eyes closed	1	2	9, 11
b) Sitting with eyes open	3	4	10
c) Dancing in open embrace		6	
d) Dancing in close embrace	15	7, 12	8, 13
e) Dancing without contact	14		
f) Dancing individually		5	

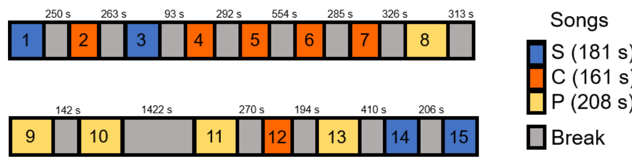

Fig. 1. Experimental protocol timeline. Refer to Table II for a description of the 15 conditions.

After each song, there was a break in which each participant filled a self-evaluation questionnaire to report the *flow* level that was experienced during the song. The flow level was reported on a 5-point scale, where 1 meant "low", and 5 "deep" flow states. Finally, taking in consideration the duration of the songs and breaks, the experimental protocol had a total duration of over 2 hours. The timeline for the experimental protocol is presented in Figure 1.

B. Data acquisition

Due to the characteristics of the experimental protocol, two wearable devices were used to acquire EEG and ECG signals. Acquisition of EEG signals was carried out with a standard EEG textile cap, dry electrodes, and an OpenBCI Cython board (OpenBCI, USA). Note that the OpenBCI board is attached to the cap. A total of 8 channels were acquired with a sampling frequency of 125 Hz. The EEG electrodes were placed over the frontal cortex with the idea of registering neuronal activity related to higher cognitive functions, the ground and bias electrodes were placed at the mastoids. The location of the electrodes according to the international 10-20 system is depicted in Figure 2. For ECG signals, we made use of the BioHarness3 (BH3) cheststrap (Zephyr Technology Corporation, USA). In addition to the EEG and ECG signals, both devices also measured triaxial acceleration, thus providing details about head and body movements. For communication, the OpenBCI uses a custom protocol over Bluetooth while the BH3 uses a standard Bluetooth protocol. To warrant an optimal reception of the data stream from the devices regardless the position of the dancers, the Bluetooth receptors for both devices were hung from the ceiling with a height of 2 m over the center of the experiment room.

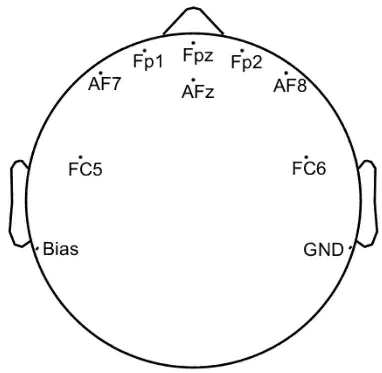

Fig. 2. EEG electrode locations according the international 10-20 system.

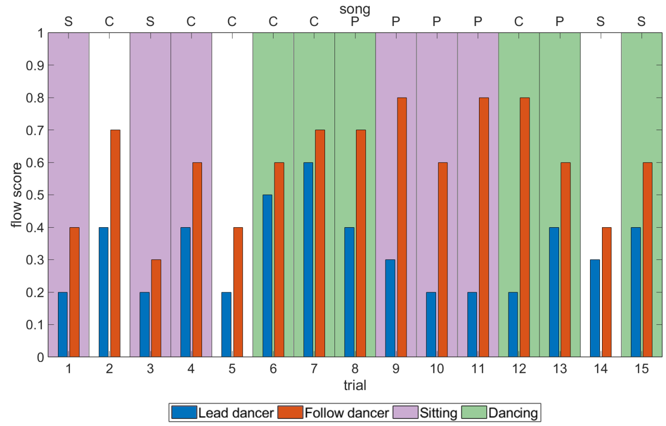

Fig. 3. Self-reported flow ratings scaled to [0,1] for lead and follow dancers. Trials are shaded by groups: Sitting or Dancing.

C. EEG pre-processing and feature extraction

EEG signals were inspected to detect and reject railed channels and discontinuities in the data steam, if any. After inspection, EEG signals were filtered with a zero-phase finite impulse response (FIR) band-pass filter with a bandwidth 0.5–30 Hz. Moreover, motivated by previous findings with the use of low-density EEG signals, [31], [32], we used the wavelet-enhanced independent component analysis (wICA) algorithm to remove artifacts and enhance the EEG signal [33].

Classical spectral power features were then extracted for each recorded channel in 8 s epochs with 4 s overlap between consecutive windows. The spectral features computed were: delta (0.5–4 Hz), theta (4–8 Hz), alpha (8–12 Hz), low-alpha (8–10 Hz), high-alpha (10–12 Hz), and beta (12–30 Hz). The power for each individual band was then normalized by the power from the fullband (0.5-30 Hz) [31]. These normalized powers were log-transformed with $10log_{10}(\,)$, so their values in dB could follow a Gaussian distribution [34].

D. ECG pre-processing and feature extraction

The ECG signal was visually analyzed to ensure good quality of QRS complex of the segments recorded. The inter-beat interval (IBI) series was extracted from the ECG signal as follows. First, the ECG was filtered using a 5^{th} order band-pass IIR filter with a bandwidth 4-40 Hz to enhance the QRS complex. This was followed by an energy based QRS detection algorithm [35], which is an adaption of the popular Pan-Tompkins algorithm [36]. Visual inspection was performed on a sub-sample of the dataset to ensure beat detection was reliable. The IBI series was further filtered to remove outliers using range based detection ($\geq$ 280 ms and $\leq$ 1500 ms), moving average outlier detection, and a filter based on percent change in consecutive RR values ($\leq 20\%$), as implemented in [37].

Various benchmark time- and frequency- domain features were then extracted [38] from the enhanced IBI series. Time domain features corresponded to mean RR, standard deviation RR (SDRR), RMSSD, and pNN50. For frequency domain analysis, first the tachogram was obtained by resampling the RR series at 4 Hz sampling frequency with cubic spline interpolation. Traditional spectral energy features were then calculated, namely low frequency (LF), high frequency (HF) and very low frequency (VLF) powers, normalized LF (LFnorm) and HF (HFnorm) powers, LF/HF ratio and total power. These features were extracted for the two dancers for each trial with 60-second windows and 45-second overlap. In case of correlation analysis with the self-reported flow scores, these features were aggregated by taking the mean over all epochs for the trial.

E. Exploratory analysis

From the extracted EEG and ECG features, the following two main aspects were explored: *(i)* the correlation was computed between features extracted from the neurophysiological signals and the self-reported flow levels under different experimental conditions; and *(ii)* the (multimodal) temporal synchrony between the two dancers under the different experimental conditions.

III. Experimental Results and Discussion

A. Flow ratings

The self-reported flow scores scaled to [0,1] are presented in Figure 3. During the experimental protocol, there were technical issues during the registering of trial #2. For the analysis, the trials were divided into two groups: sitting (trials 1, 3, 4, 9, 10 and 11), and dancing (trials 6, 7, 8, 12, 13, 15). Trials 5 and 14 were not considered in the dancing group because the conditions in these trials, dancing individually, and dancing without contact, respectively, were explicitly designed to prevent a flow state in the dancers. The Spearman's correlation values for flow scores between dancers were: 0.35 for sitting and -0.33 for dancing trial groups.

B. EEG correlates and synchrony

Regarding the quality of the EEG signals, from the visual inspection before and after signal pre-processing, we observed that most of the movement artifacts were accurately removed with the use of the bandpass filter and the wICA algorithm. This can be seen in Figure 4. To verify the

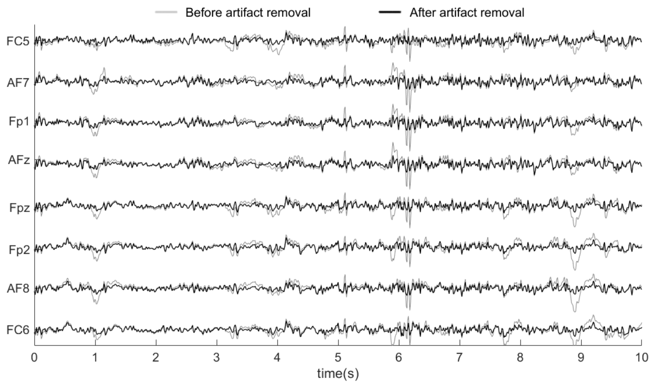

Fig. 4. Example of removal of motion artifacts in EEG signals.

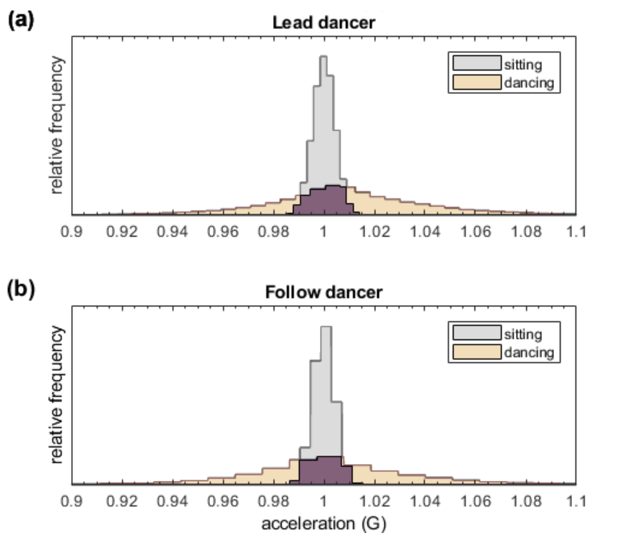

Fig. 5. Distributions of the magnitude of the acceleration vector in the sitting and dancing trials for (a) lead, and (b) follow dancers.

removal of the movement artifacts, the correlation between the magnitude of the acceleration vector and each EEG channel was computed for each song. It was found that these values were not significantly different between the sitting and the dancing trials for neither the lead nor the follow dancer. Unlike other physical activities such as running, the acceleration in the head during our experimental protocol did not present values larger than 1 G $\pm$ 0.1 G. The distributions of the magnitude of the acceleration vector in the sitting and dancing trials are shown in Figure 5.

For each dancer, the correlates between flow and EEG spectral features, calculated with Spearman's rank correlation (ρ_S), were computed for the two trial groups, namely sitting and dancing. There was one flow rating for each trial; as such, the EEG spectral features were averaged first across electrodes, and later across epochs during the trial. Figure 6 shows the Spearman's correlation values for different conditions, separately for the lead and follow dancers. It can be noted that for both dancers in the sitting condition, the highest positive correlations were obtained with spectral features in the alpha band, and the low frequency bands (delta and theta) consistently presented negative correlation values. For the dancing condition, in turn, only correlation for the

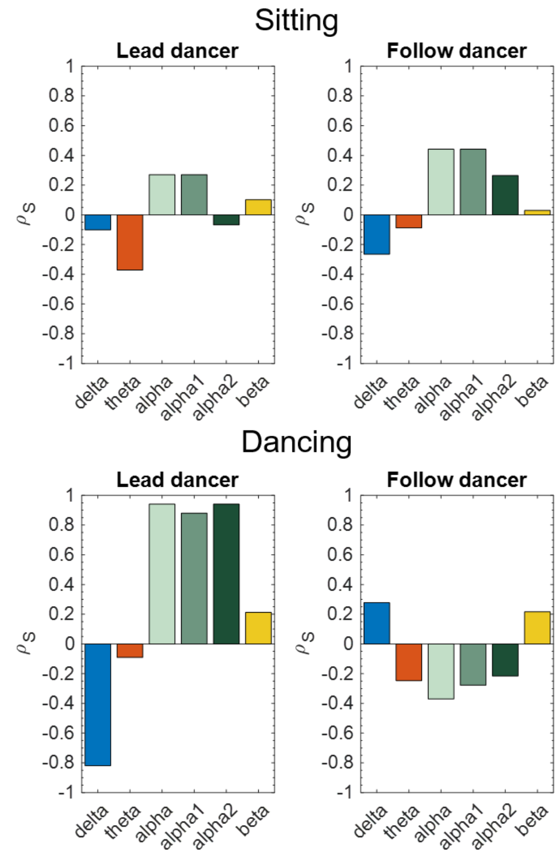

Fig. 6. Correlation between self-reported flow scores and EEG features.

spectral features in the theta and beta bands had the same sign in both dancers.

We also explored the synchrony of EEG spectral features between dancers. For this purpose, for each trial, two time series, one from the lead dancer and one from the follow dancer, were obtained for each spectral feature, and the Spearman's correlation was calculated. The ρ_S values for each spectral feature in each trial are presented in Table III. It possible to observe that all the spectral features present low ρ_S values in the sitting trials. On the other hand, on average, for the dancing trial delta and beta bands present values of $\rho_S > 0.3$.

C. ECG correlates and synchrony

The correlations between the self-reported flow scores and the HRV features for both dancers were calculated for sitting and dancing trial groups. The averaged features for each trial were compared against the flow score for that trial. Spearman's correlation of the features for both dancing and sitting trial groups for both dancers are given in Table IV. We observed that for sitting trials the correlations are generally low across all features for both the dancers. This is specially the case for time domain features while being slightly higher for frequency domain features (LF power for lead dancer and HF power for follow dancer). These features directly represent the sympatho-vagal balance of the body as well as individual activations of the sympathetic and parasympathetic systems [38]. In turn, we found higher (absolute)

TABLE III
EEG FEATURES SYNCHRONY (SPEARMAN'S CORRELATION) BETWEEN THE DANCERS ACROSS DIFFERENT TRIALS.

Trial	Song	Spectral features					
		delta	theta	alpha	alpha1	alpha2	beta
1	S	-0.13	-0.24	-0.25	-0.17	-0.10	0.28
3	S	0.02	-0.27	0.3	0.29	0.37	-0.32
4	C	0.49	-0.05	-0.07	-0.29	0.16	0.11
6	C	0.45	0.40	0.03	-0.05	0.21	0.11
7	C	0.29	0.07	0.00	-0.06	-0.13	0.62
8	P	0.53	0.14	-0.03	0.01	-0.05	0.52
9	P	0.11	-0.16	0.12	0.20	0.04	0.12
10	P	-0.40	0.22	-0.30	-0.29	-0.08	0.04
11	P	-0.06	0.07	-0.10	-0.20	-0.34	-0.03
12	C	0.53	0.12	-0.19	-0.05	0.05	0.17
13	P	0.34	0.08	-0.44	-0.17	-0.11	0.27
15	S	-0.21	-0.24	-0.19	-0.29	-0.12	-0.14
sit avg.	—	0.01	-0.07	-0.05	-0.08	0.01	0.03
dance avg.	—	0.32	0.10	-0.13	-0.10	-0.02	0.26

TABLE IV
CORRELATION BETWEEN SELF-REPORTED FLOW SCORES AND HRV FEATURES FOR BOTH DANCERS.

	Sitting		Dancing	
HRV Features	Lead	Follow	Lead	Follow
mean RR	-0.07	-0.09	-0.88	0.31
SDRR	-0.07	-0.06	-0.39	0.46
RMSSD	-0.07	0.09	-0.52	-0.49
pNN50	-0.07	-0.03	-0.52	-0.09
Total power	-0.3	-0.15	-0.64	0.31
VLF	0.27	-0.06	0.33	0.06
LF	-0.3	-0.15	-0.76	0.62
HF	-0.07	-0.44	-0.21	-0.09
LF/HF	-0.03	-0.06	-0.03	0.93
LFnorm	-0.27	-0.06	-0.03	0.93
HFnorm	0.27	0.06	0.03	-0.93

average correlations across features for the follower dancer (0.39) compared to lead dancer (0.47).

We explored the synchrony between the dancers in two ways. First, we calculated the synchrony at the time series level by calculating the Spearman's correlation between the tachograms (tacho) of the two dancers. We also calculated synchrony at the HRV feature level. This was done by first creating a time series of the HRV feature epochs over a given trial for both dancers followed by calculating the Spearman's correlation between the dancers. The time series and feature level synchrony for the different condition-song pairs are shown in Table V. On average, the correlations between the time series and feature level synchrony were higher for dancing conditions than sitting conditions. The highest tachogram series synchrony was achieved for trial #6 (dancing in open embrace, song Cascabelito). We observed the highest average correlations for dancing for mean RR (0.97), sdRR (0.91) and pNN50 (0.73) features.

As can be seen, alpha band powers showed the highest correlations with flow, thus corroborating findings in [18]. Interestingly, alpha band powers have also been reported in meditation/relaxation, thus motivating future work on the effects of Argentine tango and mindfulness. Moreover, the HRV correlations during dancing showed the importance of the metric to gauge dancer emotional states, inline with findings from [21], [22]. While the activity of dancing may have caused a natural change in heart rate activity, the correlation changes between lead and follow dancers suggest the relationship may be more than just an effect of movement. Overall, this case study has suggested that it is possible to monitor dancer physiological signals in an unobtrusive manner, thus opening the door for future studies. While the findings here have been based on a small sample size, the obtained findings are promising.

IV. CONCLUSIONS

This article presented a case study of a multimodal-hyperscanning project where EEG and ECG signals were simultaneously acquired from lead and follow dancers during a session Argentine tango. Such project was possible due to the use of portable devices which are light and comfortable to wear. Although the execution of movement introduced artifacts (specifically in the EEG signals), these were effectively removed with artifact removal algorithms. Despite the fact that the small sample size hindered the generalization of the outcomes herein presented, the observed correlates with flow and inter-dancer synchrony during dancing suggest that multimodal hyperscanning is possible and the open doors to future studies involving correlates to perceived levels of depression and stress during dancing therapy.

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TABLE V

HEART RATE AND HRV SYNCHRONY (SPEARMAN'S CORRELATION) BETWEEN THE DANCERS ACROSS DIFFERENT TRIALS.

Trial	Song	HRV features											
		tacho	**mean RR**	**SDRR**	**RMSSD**	**pNN50**	**Total power**	**VLF**	**LF**	**HF**	**LF/HF**	**LFnorm**	**HFnorm**
1	S	0.1	0.27	-0.04	-0.01	0.16	0.06	0	0.16	0.36	0.57	0.54	0.54
3	S	-0.09	-0.53	0.47	-0.3	-0.86	-0.04	0.55	-0.18	0.51	-0.25	0	0
4	C	0.22	0.85	0.63	0.02	0.12	-0.28	0.67	-0.45	0.04	-0.15	-0.02	-0.02
6	C	0.87	0.98	0.91	0.82	0.93	0.42	0.05	0.69	0.92	-0.67	-0.64	-0.64
7	C	0.76	0.98	0.94	0.87	0.77	0.07	0.02	0.59	0.81	0.79	0.63	0.63
8	P	0.82	1	0.97	0.02	0.8	0.29	0.51	0.59	-0.01	-0.28	-0.17	-0.17
9	P	-0.03	-0.43	-0.34	-0.76	-0.6	-0.3	0.56	-0.39	-0.22	-0.52	-0.64	-0.64
10	P	0.07	0.8	0.56	0.69	0.42	0.29	0.03	0.39	-0.55	0.92	0.54	0.54
11	P	0.05	-0.16	-0.62	-0.28	-0.66	-0.65	-0.41	-0.71	0.29	-0.6	-0.76	-0.76
12	C	0.7	1	0.96	0.97	0.92	0.48	-0.07	0.73	0.99	0.05	0.78	0.78
13	P	0.78	0.99	0.88	0.09	0.76	0.95	0.73	0.97	0.8	0.04	-0.16	-0.16
15	S	0.78	0.84	0.78	-0.75	0.22	-0.65	0.17	-0.36	0.03	0.55	0.67	0.67
sit avg.	—	0.05	0.13	0.11	-0.11	-0.24	-0.15	0.23	-0.2	0.07	-0.01	-0.06	-0.06
dance avg.	—	0.79	0.97	0.91	0.34	0.73	0.26	0.24	0.54	0.59	0.08	0.19	0.19

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