Ph.D. Defense
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Learning and Understanding Partner Dance through Motion Analysis in Virtual Environment

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University of Cyprus, Cyprus

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Outline

Introduction

State of the art

Chapter 1: Salsa motion modeling

Chapter 2: Musical motion feature evaluation

Chapter 3: Virtual reality salsa dance application

Conclusion

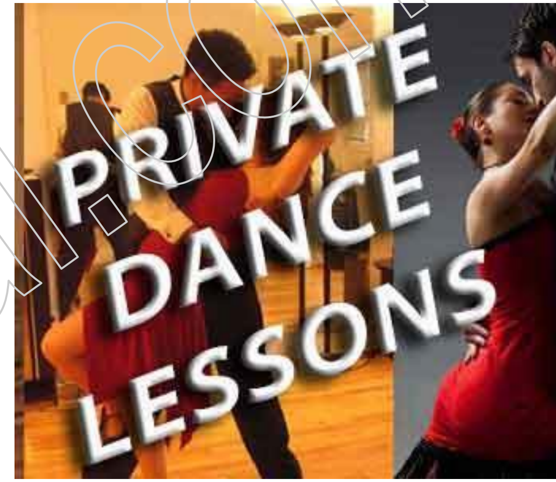
Introduction

Physical activity

Artistic activity

Social: “Break the ice”

Worldwide Community



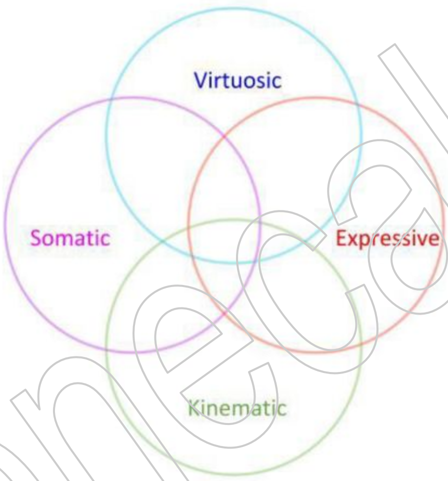
How to learn ?

Private class
Collective classes
Festival classes
Shows / projects
Youtube

Introduction

Learning challenges:

- Collective classes
- Time and location
- Teacher weaknesses
- Practice partner
- Universal description



Virtuosic: ability to perform complex movement phrases

Somatic: ability to expand attention of external and internal influences on movement, integration of mind and body.

Kinematic: ability to articulate the mechanics of movement

Expressive: ability to communicate through movement

©Shannon Cuykendall, 2017

Motion analysis challenges:

- Oral knowledge
- Difficulty to **classify** and **index** such movements
- Digitization of the cultural heritage

Cuykendall, S. (2016). *Untying the Knot of Dance Movement Expertise: An Enactive Approach*. A body of knowledge: Embodied cognition and the arts.

Introduction

A virtual reality dance simulation that embed a virtual partner which analyzes the movement of the dance student and provide positive feedback to improve her/his dance skills

- Practice at home, alone or with other person, with flexible schedule
- Learn dance skills in an objective, reproducible and efficient way
- Custom feedback personalized for each users
- A method to digitize and archive partner dance

Introduction

A dance skills motion learning system

RQ 1: What are the important dance skills ?

RQ 2: How to evaluate a salsa performance ?

RQ 3: How to teach and how to evaluate learning ?

An interactive simulation of partner dance

RQ 4: How to synthesize a salsa dance motion for a 3D avatar ?

RQ 5: How to simulate the interaction with a virtual partner ?

RQ 6: How to simulate dance sequences ?

Introduction

Scope and related areas

Motion analysis

Animation

Physical modelling

Psychological interaction parameters

Music

Learning systems

Potential applications

Education

Behaviour recognition

Gaming

Medical

Psychology

Literature review

Author	Title	Method	Result	Limitation
Aristidou, A. (2013, 2014, 2015)	**Contemporary dance emotion expression recognition**	86 LMA-inspired features 2-dim **emotions** (8 emotions) ML: RF and SVM on a database	RF: **80-90%** recognition	Contemporary dance only. LMA very abstract.

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Niewiadomski, R. (2019)	**Analysis of Movement Quality in Full-Body Physical Activities**	**Karate's Kata** movement **qualities**. Framework DANCE. Biomechanical efficiency, Shape, Intrapersonal coordination. 16 measurements => global movement quality score	Correlation with expert annotation: Pcc = **84%**.	Martial art only. Aesthetic aim.

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Fourati, N. (2014, 2015)	**Body cues for the classification of body expression in daily actions**	114 features from anatomy, direction and postures. Classify emotion in **daily action** (Walk, Sit down, Lift, Throw). Reduction to **11 features**: 2 acceleration 5 posture 3 speed 1 standard deviation.	RF: 67% to **97%**.	Abstract features.

Literature review

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Oczimder, K. (2018)	**Perceiving Artistic Expression: A Formal Exploration of Performance Art Salsa**	Dance sequence = motion primitives over 8-beat **Energy** and **Phrase complexity** as metrics. Four dance sequences => 20 motion primitives. 15 **judges Vs AI** judge using the transition model.	**81%** correlation for artistical merit.	Aesthetic aim.

Literature review

Introduction | **SoA** | Chapter 1 | Chapter 2 | Chapter 3 | Conclusion

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Mousas, C. (2018)	**Virtual reality interactive Salsa dance**	Hidden Markov model to **predict** the virtual partner dance behavior. Each animation that follows the current one is **generated** based on a hidden markov model and an **initial database**.	Q: **naturalness of avatar motion**. Hand contacts are beneficial.	Relative appreciation. Approximation. Lack of expert review

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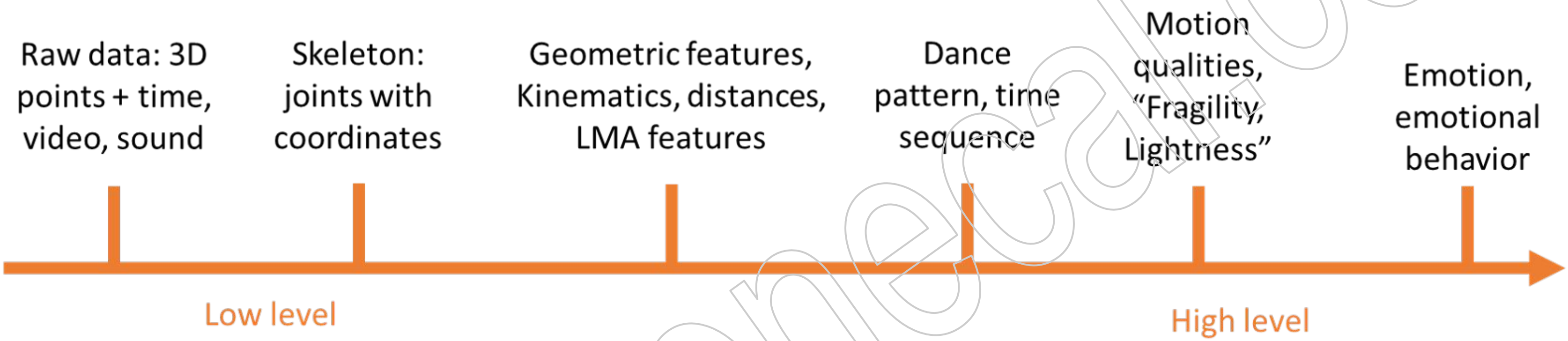
Dos Santos, A. (2017, 2018)	**You Are Off The Beat!: Is Accelerometer Data Enough for Measuring Dance Rhythm?**	RiMoDe, tracks physical **rhythmic abilities**. Acceleration peak time: "**time between peaks**." **Six themes** are identified as necessary in this context: Synchronicity, Weight transfer, Limbs/Joints, Quality of the movements, Posture, Gaze.	Results show a **major gap** between the purely algorithmic approach and how experts evaluate dance rhythm.	Tracked feature is not sufficient alone

Literature review

Considerations from the SOA:



Except rhythm, lots of **aesthetic** evaluation

LMA or **multi-feature** system, but less music-synchronized feature.

Learning needs **repetitions** for the motions.

Inverse kinematic allows control of end-effectors. No full description of the dance motion

Modelling of the interaction but still from an external point of view

No description of **dance sequences**, from teacher point of view

Chapter 1:
Salsa motion modeling : building the Musical Motion Features

Chapter 1

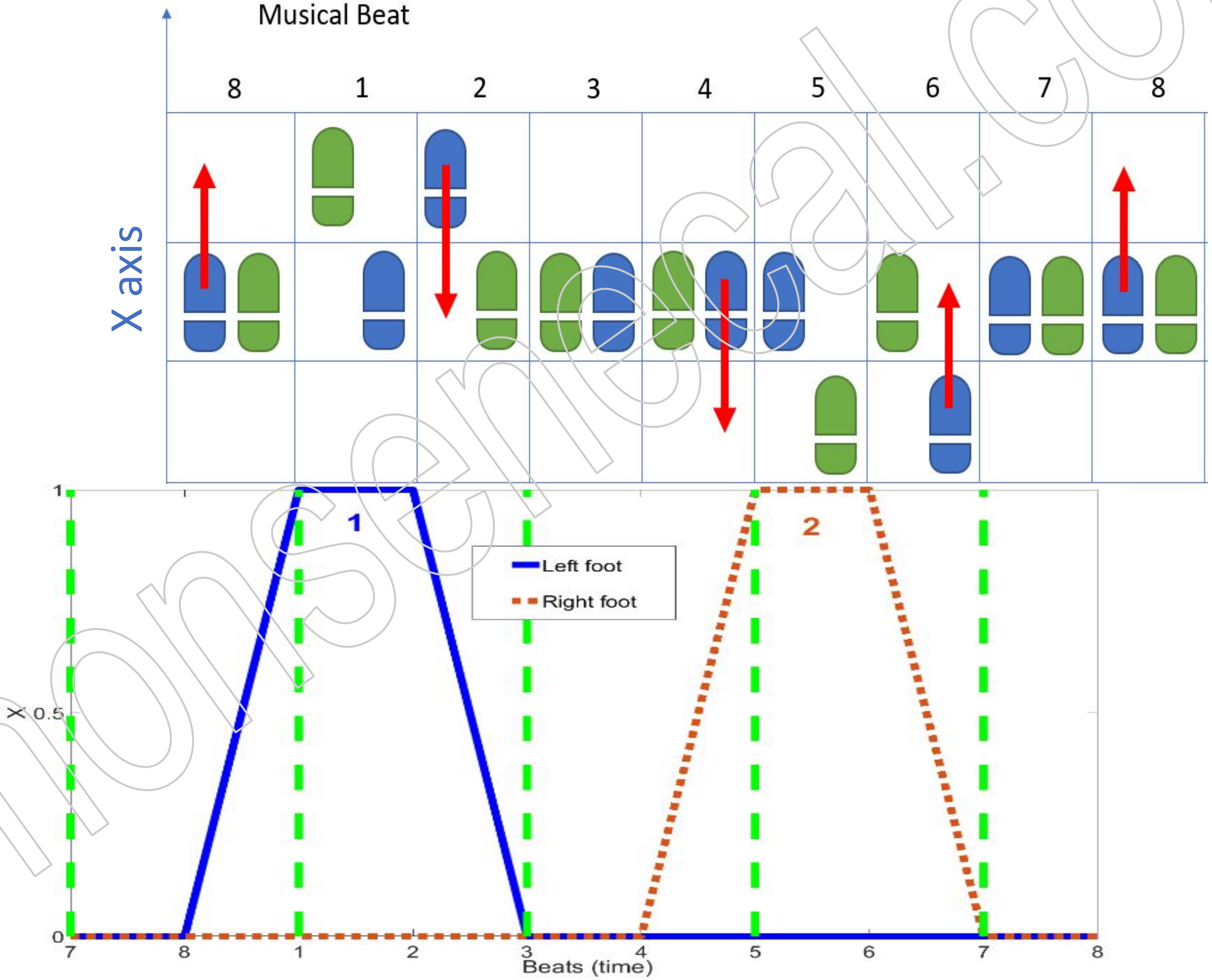
Field study:

- Experts from Salsa dance
- Questionnaire resulting in 6 important criteria for learning

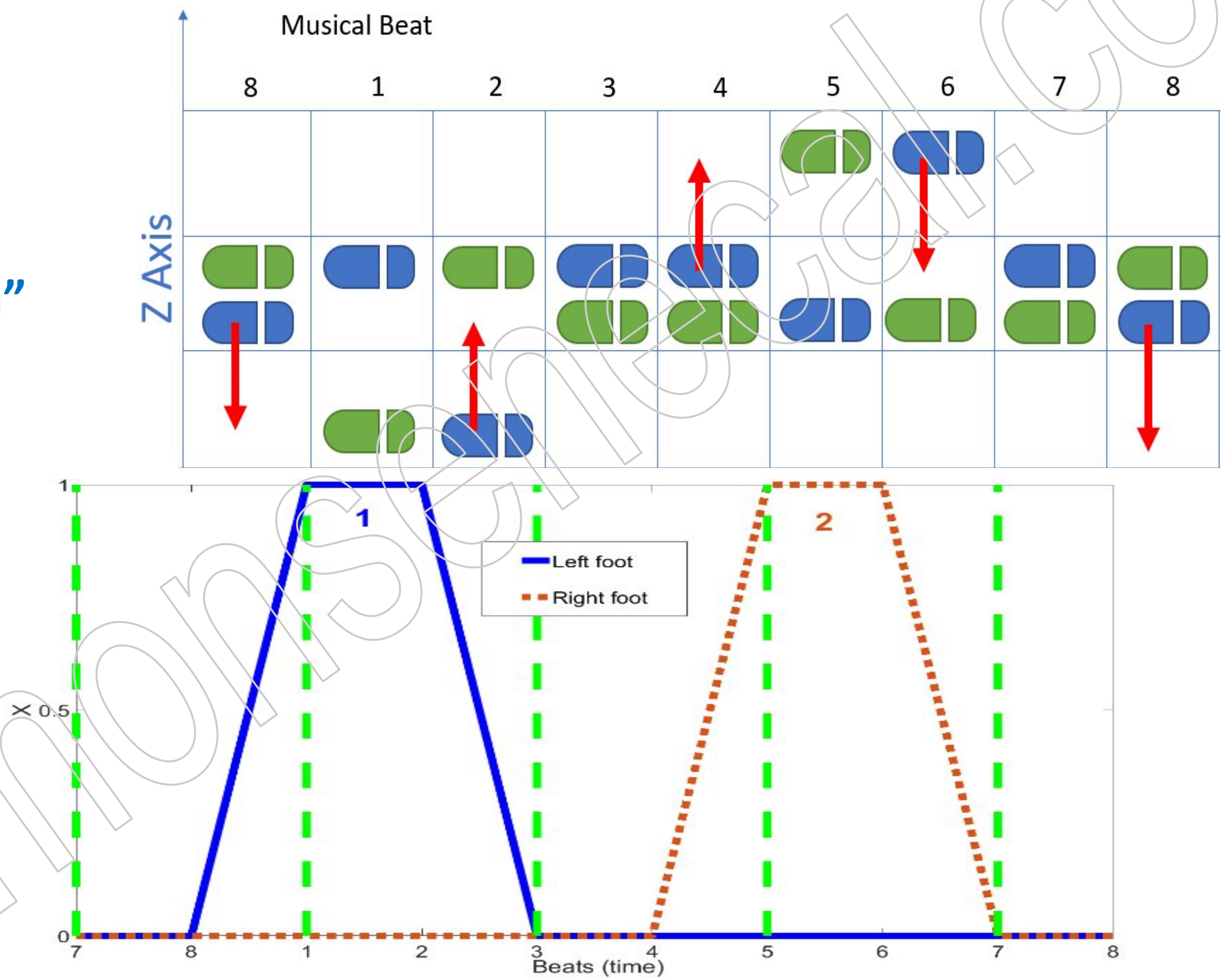
Dance skills	Definition	Importance
Rhythm	Being **synchronized** with the music's tempo. Dancing on the rhythm.	10
Guidance	Being able to **lead or follow** her/his partner	7
Fluidity	Being able to move **smoothly** on the music	6
Styling	Adding your **own variation** to the basic movements. Use of more hand gestures.	5
Sharing	Being able to **share** the moment and enjoy the dance	7
Musicality	Using your own dance movement **with the music's** variation	3

Salsa motion modelling

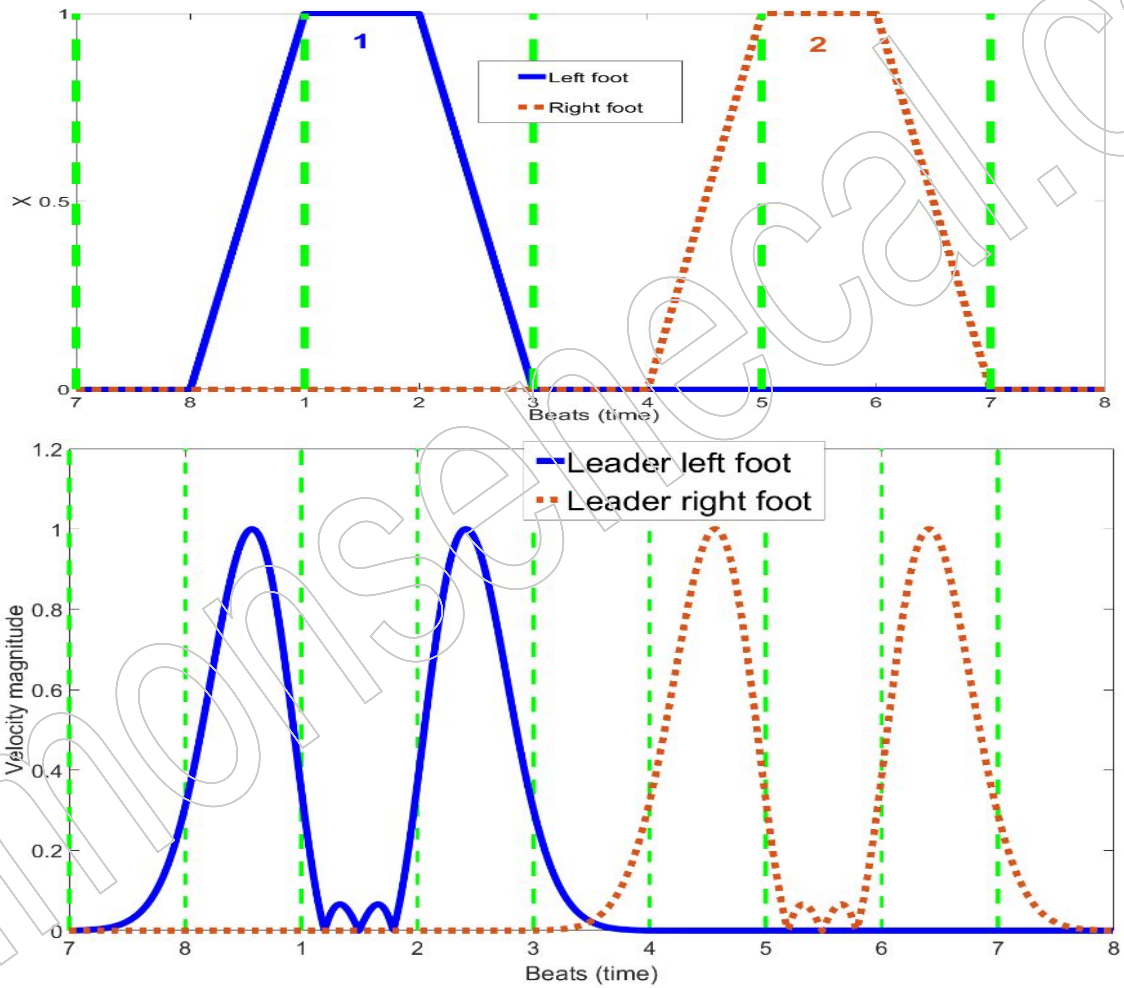
"Mambo"



"Cucaracha"


Musical Beat
8
1
2
3
4
5
6
7
8
Z Axis
1
2
Left foot
Right foot
1
X 0.5
0
7
8
1
2
3
4
5
6
7
8
Beats (time)

Velocity analysis

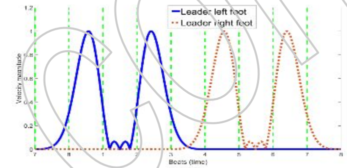


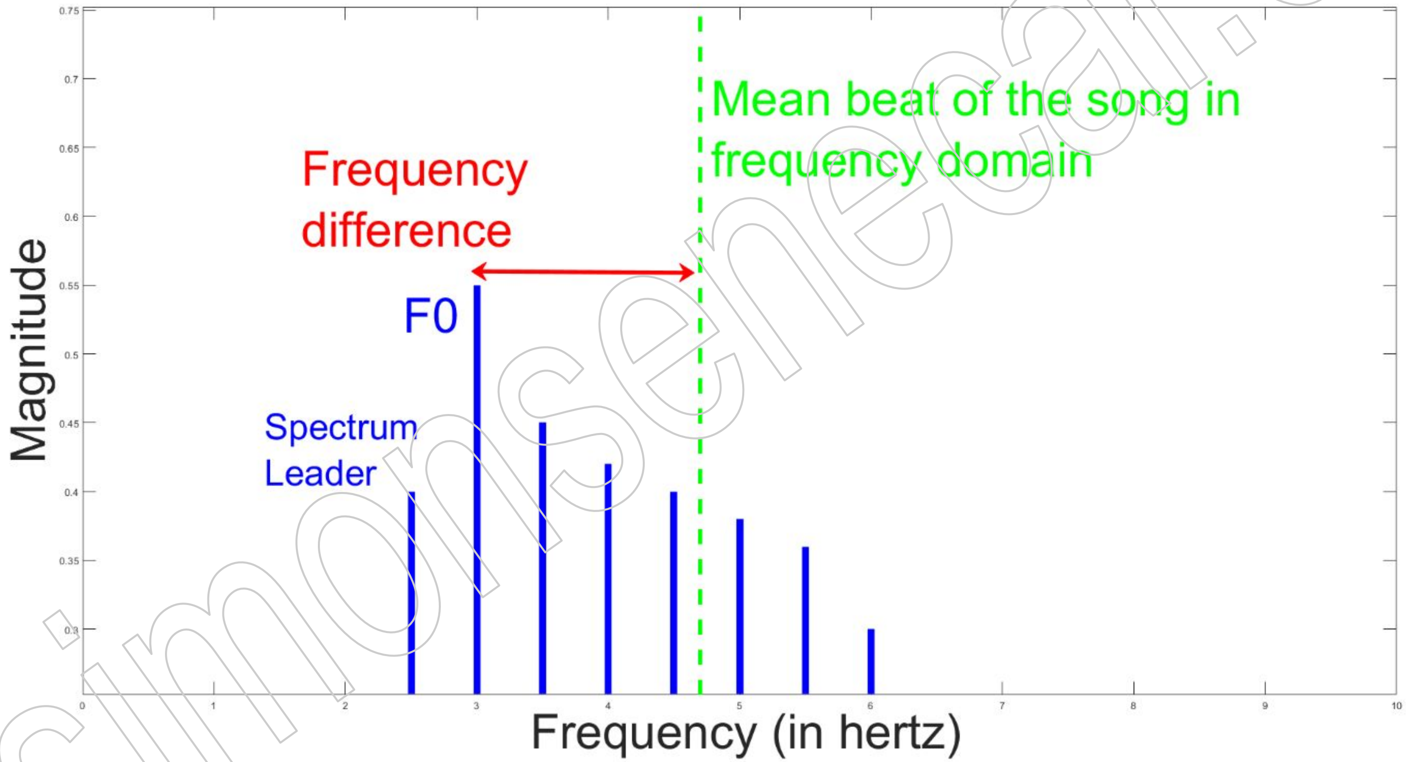
Theoretical location of the foot motion !

Chapter 1

Spectrum

Merging the feet velocity profile (periodic)
180bpm = 3Hz

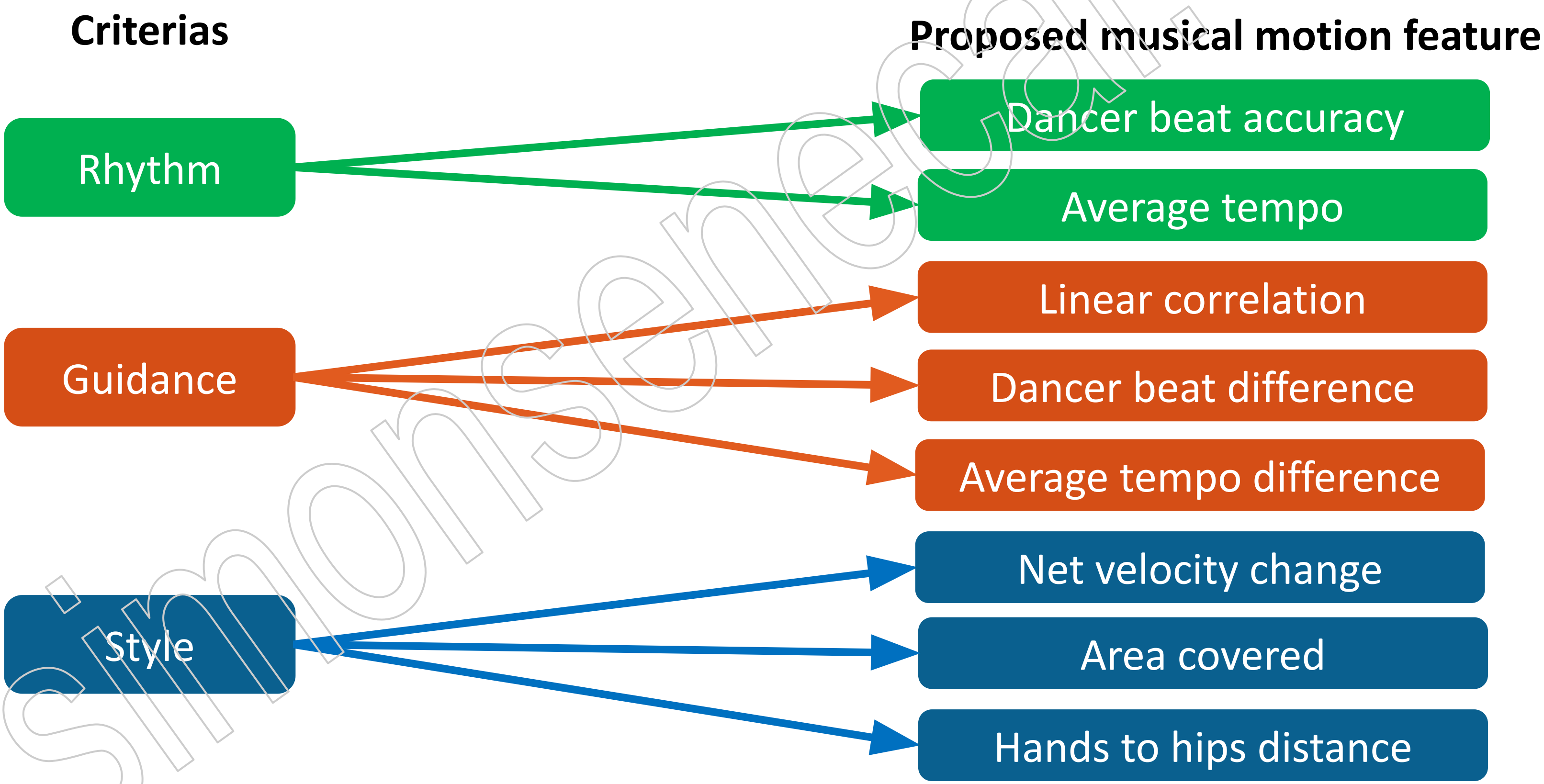




Chapter 1

Musical Motion Feature (MMF):

Set of features considering motion and music synchronization able to describe a human motion in terms of dance skills.



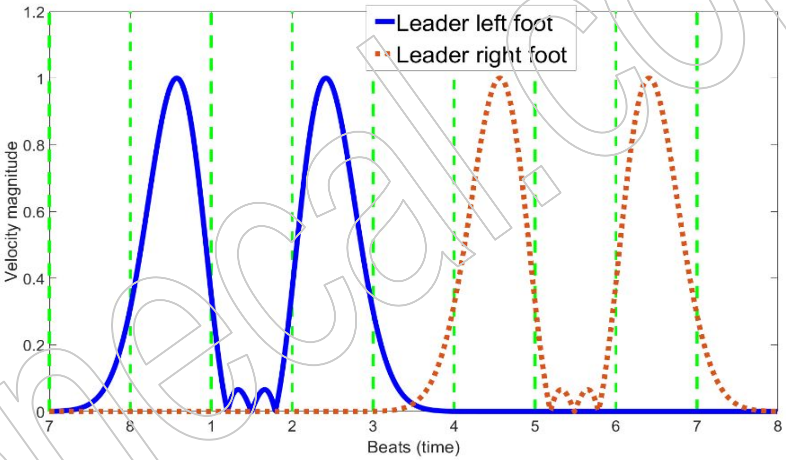
Criteria 1 – Rhythm

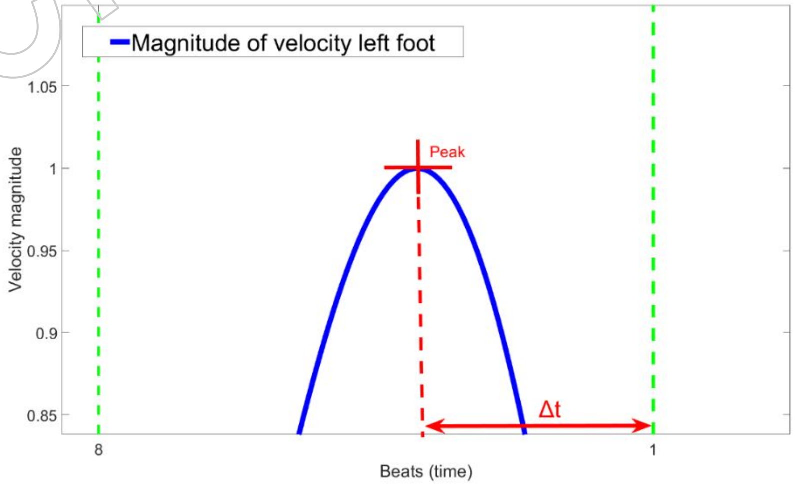
Time difference between the music's beat and the dancer's beat.

$$T_{diff} = Abs\left(\begin{matrix} t(vel\_peak)_{b8<t<b1} \\ -(t_{beat1} - \Delta t) \end{matrix}\right)$$

- For each danced beat (4)
- For each partner (2)

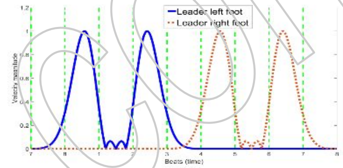
=> 8 measurements





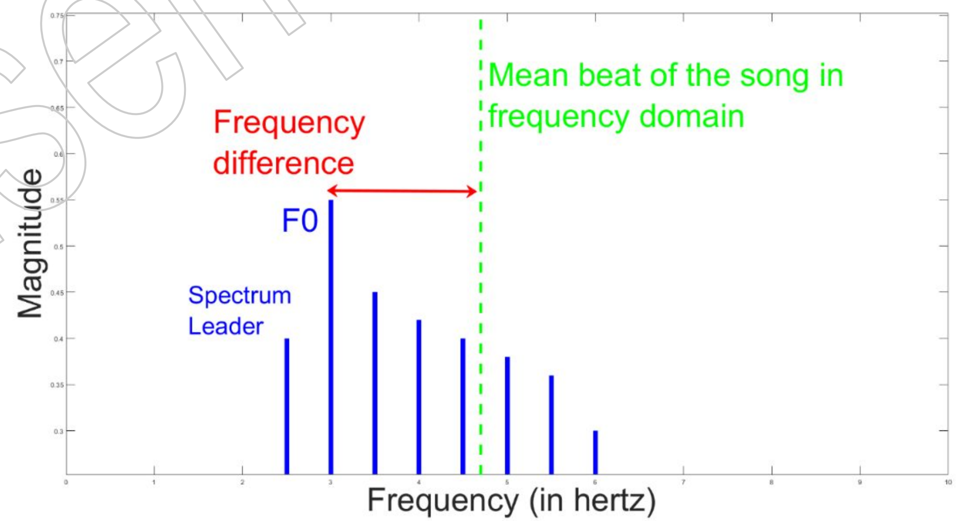
Chapter 1

Criteria 1 – Rhythm



The average frequency of the dancer foot is compared with the main frequency of the music.

$$Avg_{tempo} = Abs\left(\begin{array}{c} f_0[fft(vel_{lf} + vel_{rf})] \\ -f_{music} \end{array}\right)$$



=> 2 measurements

Criteria 2 – Guidance:

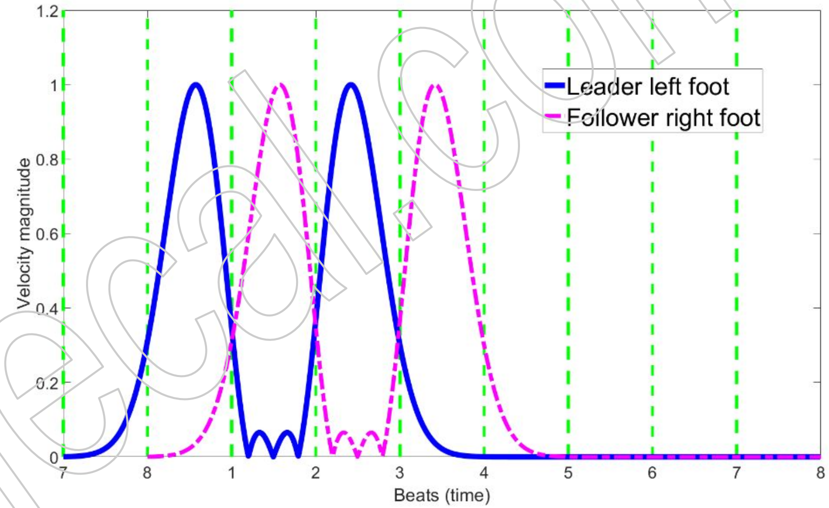
A time offset will naturally occur for the two feet of the follower and leader.

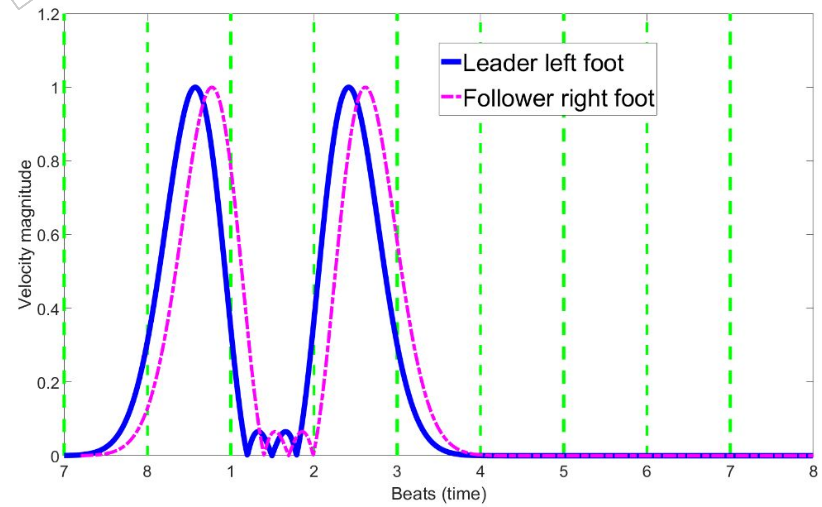
The linear correlation of velocity is computed between dancers:

$$r = \frac{\sum_m \sum_n (A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\left(\sum_m \sum_n (A_{mn} - \bar{A})^2\right)\left(\sum_m \sum_n (B_{mn} - \bar{B})^2\right)}}$$

where $\bar{A}$ = mean2(A), and $\bar{B}$ = mean2(B).

=> 2 measurements





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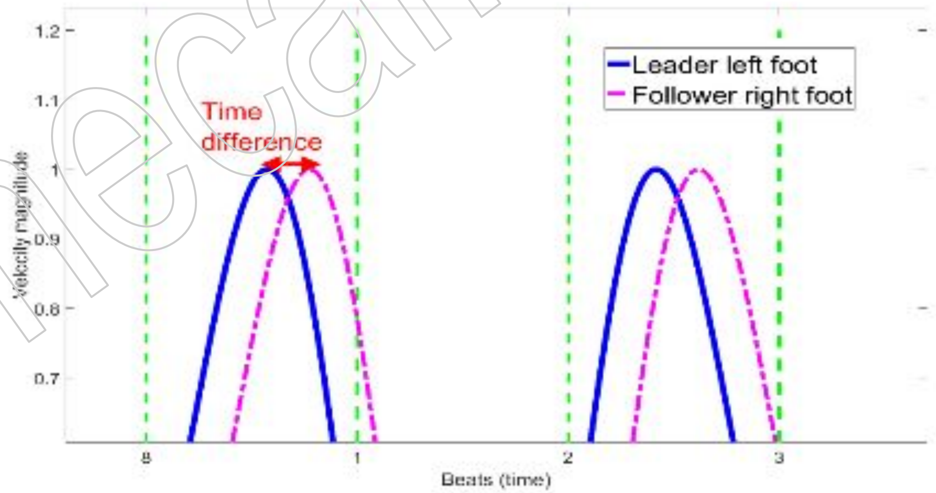
=> 2 measurements



The time difference is an indices on the connection between dancer within the couple:

$$T_{diff} = Abs\begin{pmatrix} t[(vel\_peak)_{b8<t<b1}]_{leader} \\ -t[(vel\_peak)_{b8<t<b1}]_{follower} \end{pmatrix}$$

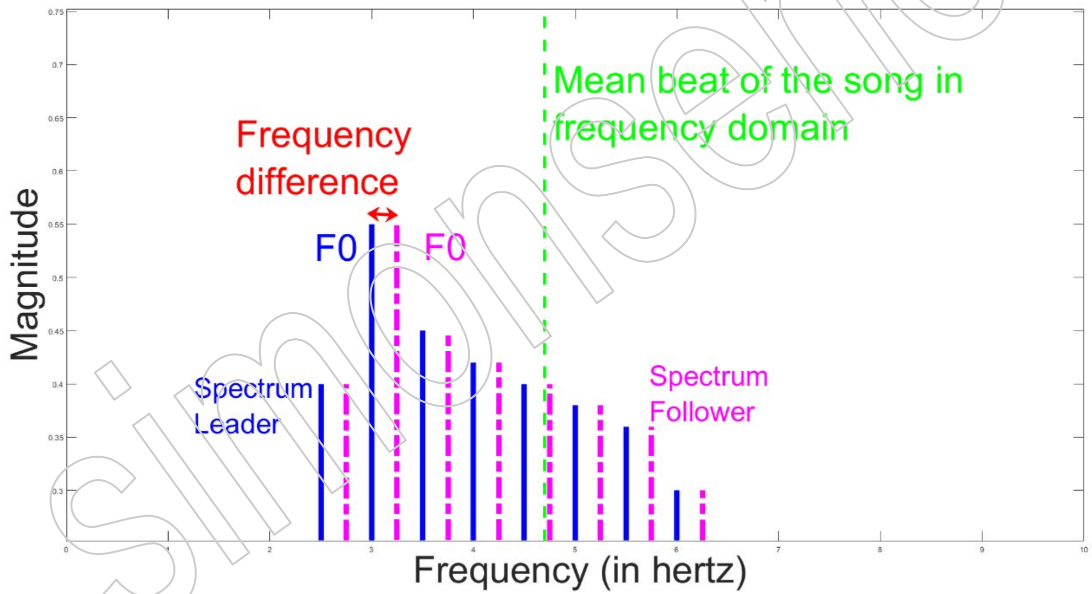
=> 4 measurements

Chapter 1

Criteria 2 – Guidance:

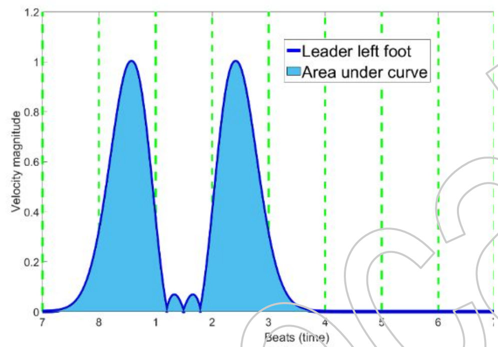
The difference between the two main tempo danced over one song.

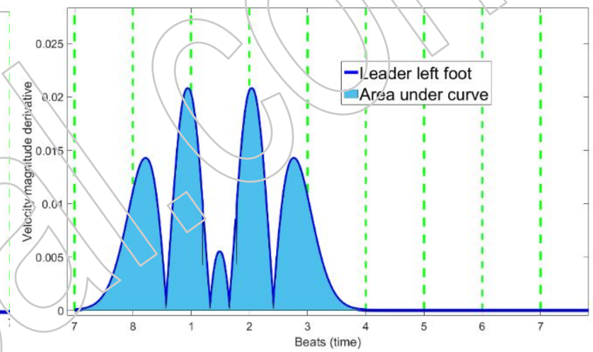
$$Avg_{tempo} = Abs\begin{pmatrix} f_0[fft(vel_{lf} + vel_{rf})_{leader}] \\ -f_0[fft(vel_{lf} + vel_{rf})_{follower}] \end{pmatrix}$$



=> 1 measurement

Criteria 3 – Styling:





Area covered: during the dance.
Witness of better dance control

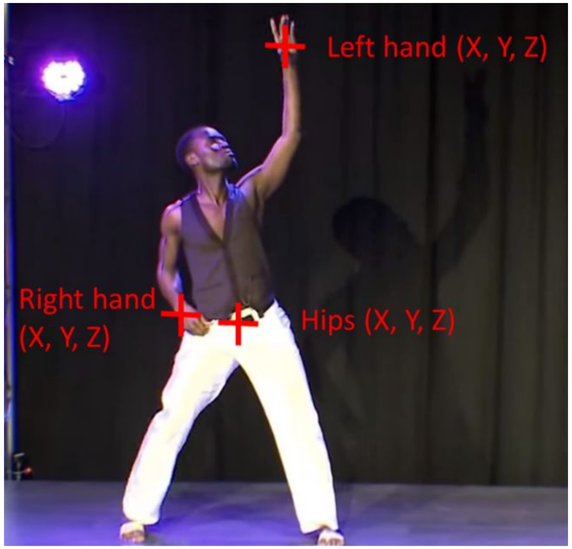
$$Area\ Covered = \int Velocity\ dt$$

=> 4 measurements

Net velocity change: During the dance, quantity of efforts.

$$Net\ Velocity\ Change = \int Acceleration\ dt$$

=> 4 measurements



The mean distance between hips and hands reflects if the dancer moves his hands to make some styling effect.

$$Handsmovement = Average_{8beat}\left(\sqrt{(X_{hand} - X_{hips})^2 + (Y_{hand} - Y_{hips})^2 + (Z_{hand} - Z_{hips})^2}\right)$$

=> 4 measurements

Rhythm

μ_j	Skill	MMF	Definition
μ_1	Rhythm	Feet rhythmic accuracy	$Abs[t(vel.\ peak_{L.F.\ leader}(beat_1)) - t(beat_1) - \Delta t]$
μ_2	Rhythm	Feet rhythmic accuracy	$Abs[t(vel.\ peak_{L.F.\ leader}(beat_3)) - t(beat_3) - \Delta t]$
μ_3	Rhythm	Feet rhythmic accuracy	$Abs[t(vel.\ peak_{R.F.\ leader}(beat_5)) - t(beat_5) - \Delta t]$
μ_4	Rhythm	Feet rhythmic accuracy	$Abs[t(vel.\ peak_{R.F.\ leader}(beat_7)) - t(beat_7) - \Delta t]$
μ_5	Rhythm	Feet rhythmic accuracy	$Abs[t(vel.\ peak_{R.F.\ follower}(beat_1)) - t(beat_1) - \Delta t]$
μ_6	Rhythm	Feet rhythmic accuracy	$Abs[t(vel.\ peak_{R.F.\ follower}(beat_3)) - t(beat_3) - \Delta t]$
μ_7	Rhythm	Feet rhythmic accuracy	$Abs[t(vel.\ peak_{L.F.\ follower}(beat_5)) - t(beat_5) - \Delta t]$
μ_8	Rhythm	Feet rhythmic accuracy	$Abs[t(vel.\ peak_{L.F.\ follower}(beat_7)) - t(beat_7) - \Delta t]$
μ_9	Rhythm	Average tempo	$Abs(FFT(vel._{L.F.\ leader} + vel._{R.F.\ leader})(f_0) - tempo(Hz))$
μ_{10}	Rhythm	Average tempo	$Abs(FFT(vel._{L.F.\ follower} + vel._{R.F.\ follower})(f_0) -$ $tempo(Hz))$

Guidance

μ_{11}	Guidance	Linear Correlation	$Corr(vel._{L.F.\ leader}, vel._{R.F.\ follower})$
μ_{12}	Guidance	Linear Correlation	$Corr(vel._{R.F.\ leader}, vel._{L.F.\ follower})$
μ_{13}	Guidance	Feet Rhythmic difference	$Abs[t(vel.\ peak_{L.F.\ leader}(beat_1)) - t(vel.\ peak_{R.F.\ follower}(beat_1))]$
μ_{14}	Guidance	Feet Rhythmic difference	$Abs[t(vel.\ peak_{L.F.\ leader}(beat_3)) - t(vel.\ peak_{R.F.\ follower}(beat_3))]$
μ_{15}	Guidance	Feet Rhythmic difference	$Abs[t(vel.\ peak_{R.F.\ leader}(beat_5)) - t(vel.\ peak_{L.F.\ follower}(beat_5))]$
μ_{16}	Guidance	Feet Rhythmic difference	$Abs[t(vel.\ peak_{R.F.\ leader}(beat_7)) - t(vel.\ peak_{L.F.\ follower}(beat_7))]$
μ_{17}	Guidance	Average tempo diff	$Abs(FFT(vel._{L.F.\ leader} + vel._{R.F.\ leader})(f_0) - FFT(vel ...)(f_0))$

Style

μ_{18}	Styling	Net Velocity change	$\int Acceleration_{left\ foot\ leader}\ dt^2$
μ_{19}	Styling	Net Velocity change	$\int Acceleration_{right\ foot\ leader}\ dt^2$
μ_{20}	Styling	Net Velocity change	$\int Acceleration_{left\ foot\ follower}\ dt^2$
μ_{21}	Styling	Net Velocity change	$\int Acceleration_{right\ foot\ follower}\ dt^2$
μ_{22}	Styling	Area covered	$\int Velocity_{left\ foot\ leader}\ dt$
μ_{23}	Styling	Area covered	$\int Velocity_{right\ foot\ leader}\ dt$
μ_{24}	Styling	Area covered	$\int Velocity_{left\ foot\ follower}\ dt$
μ_{25}	Styling	Area covered	$\int Velocity_{right\ foot\ follower}\ dt$
μ_{26}	Styling	Hands movement	$(Euclidean\ distance(Right\ hand, Hips))_{Leader}$
μ_{27}	Styling	Hands movement	$(Euclidean\ distance(Left\ hand, Hips)_{Leader}$
μ_{28}	Styling	Hands movement	$(Euclidean\ distance(Right\ hand, Hips)_{follower}$
μ_{29}	Styling	Hands movement	$(Euclidean\ distance(Left\ hand, Hips)_{follower}$

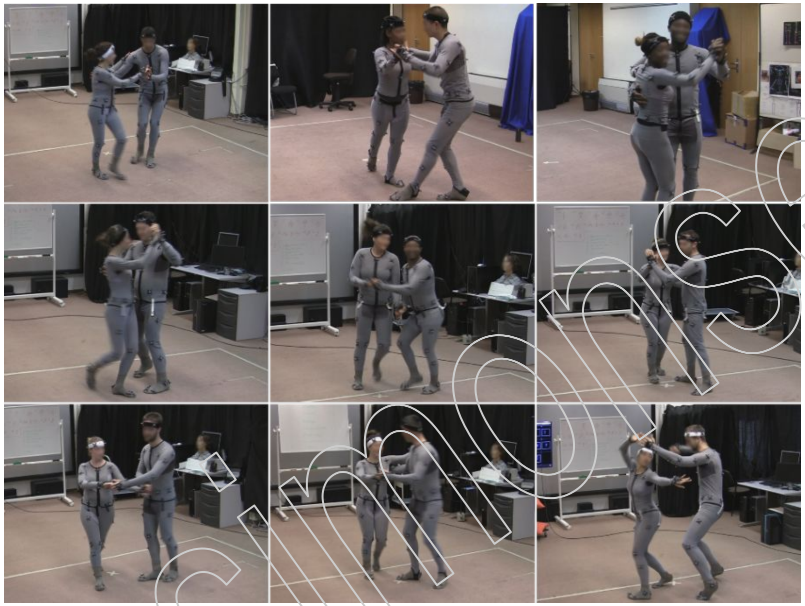
Chapter 2:
Musical motion feature evaluation

Chapter 2

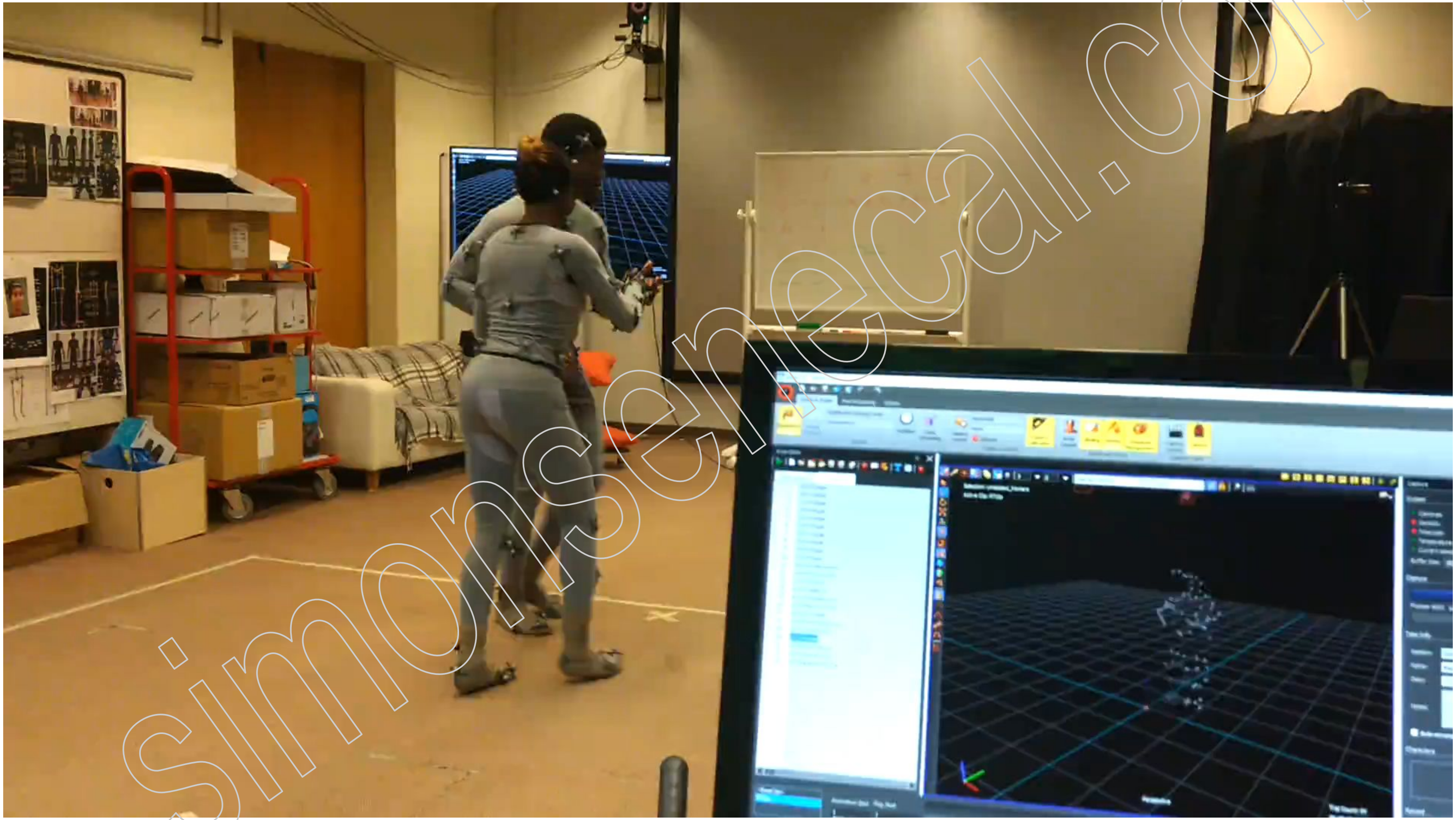
SALSA Database:

Database motion capture of two partners Salsa dance with different tempos.

Parameter	Proposed values
Type of music	Commercial music and computer-generated. (10 CG and 8 commercial)

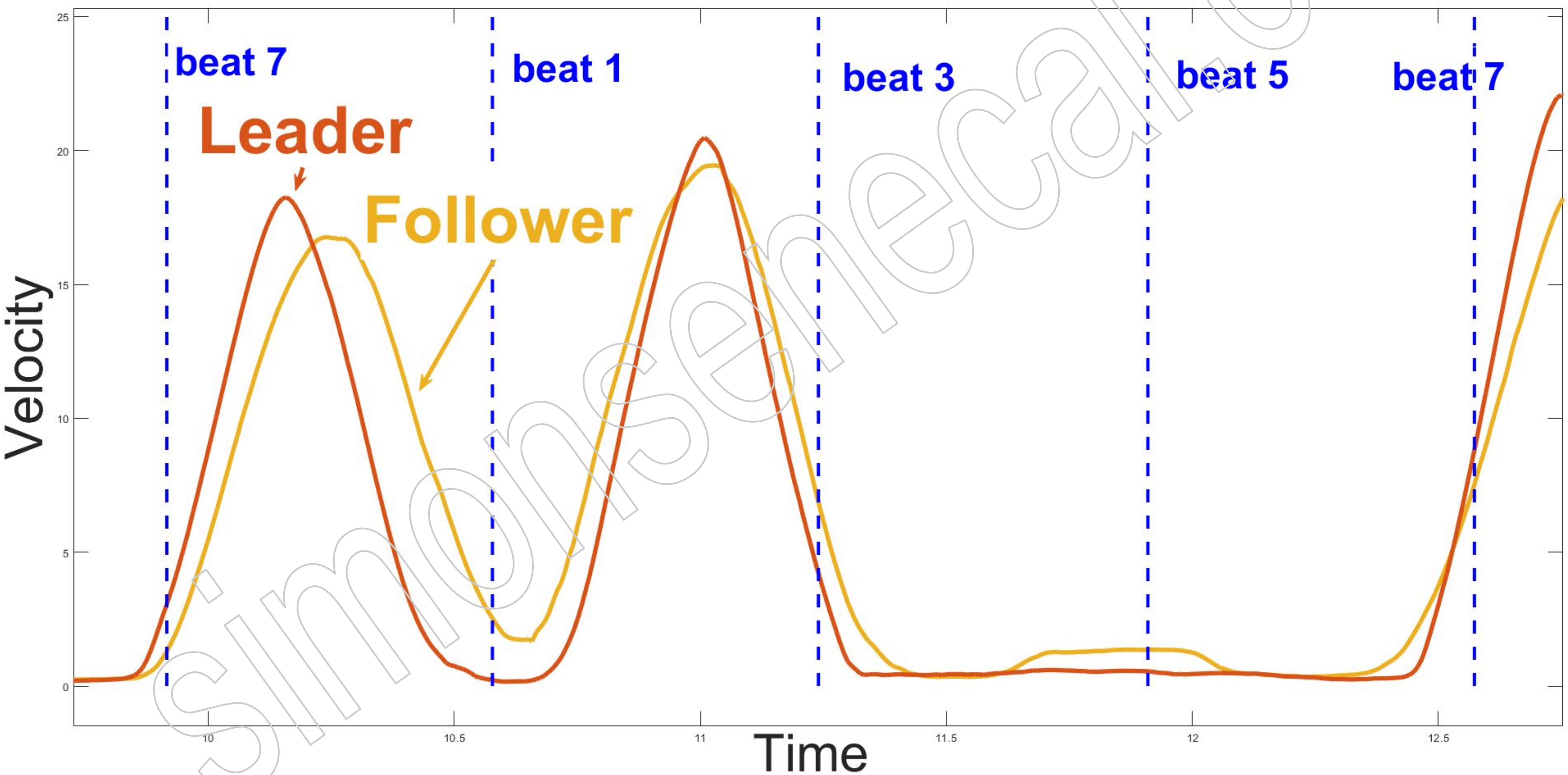


Chapter 2



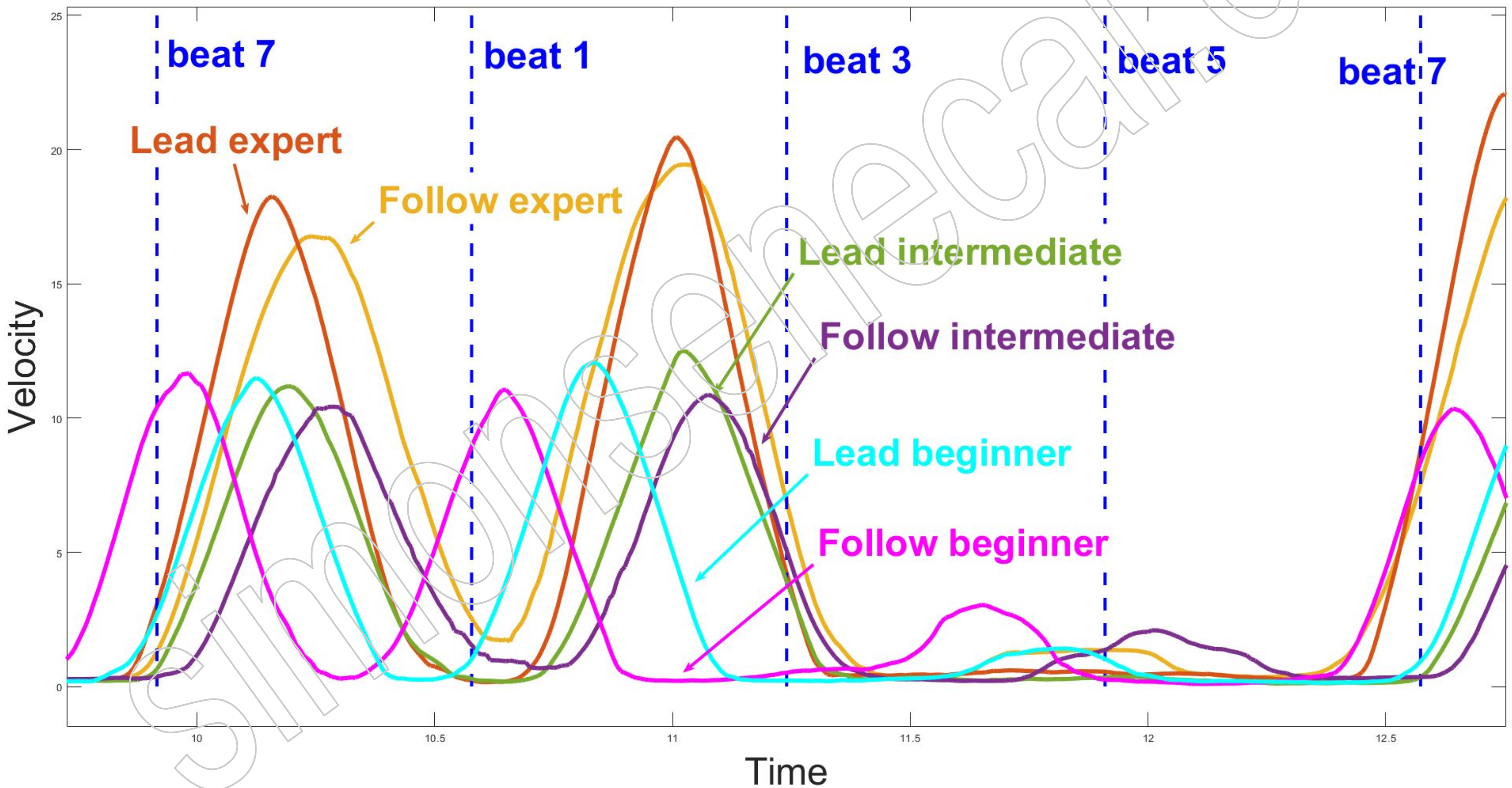
Chapter 2

First look at the database:

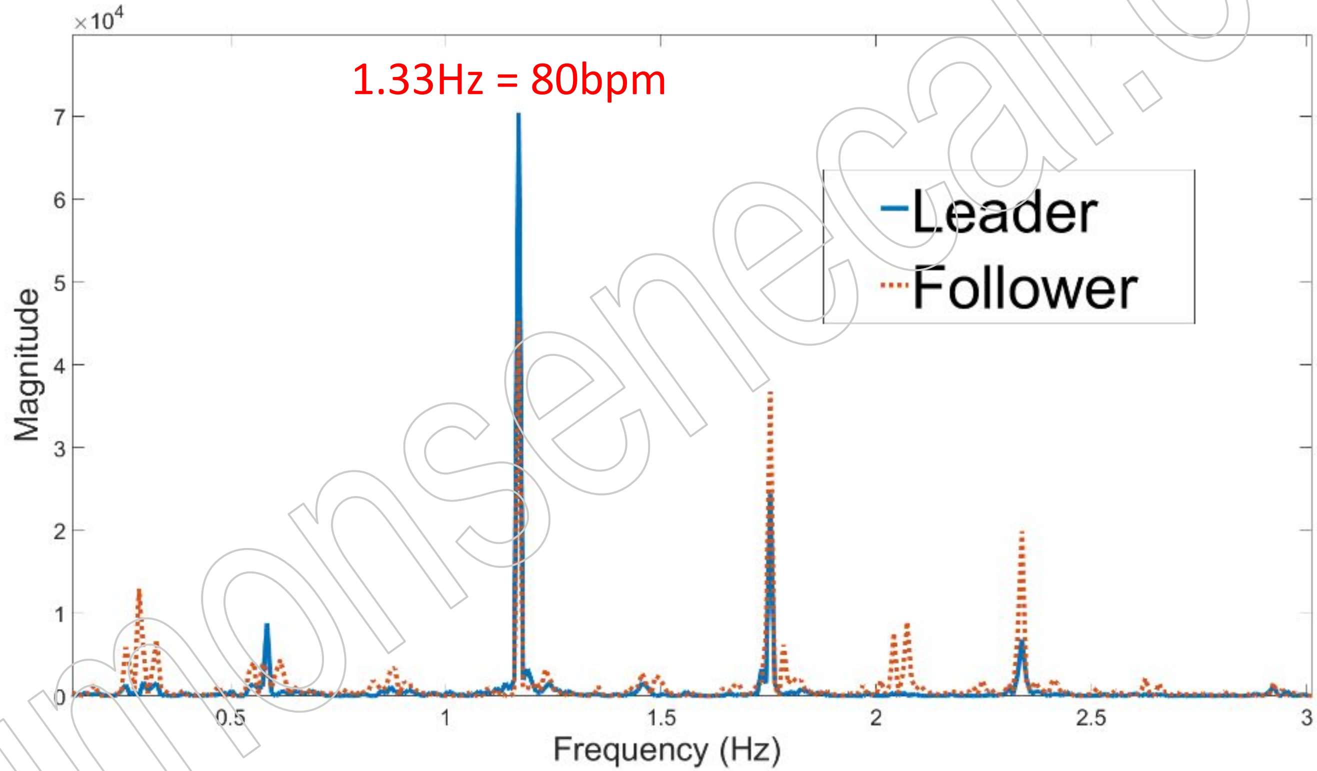


Chapter 2

Velocity profile of the feet from couples of different levels: beginner, expert and intermediate (Experimental sample). That sample corresponds to our theoretical model.



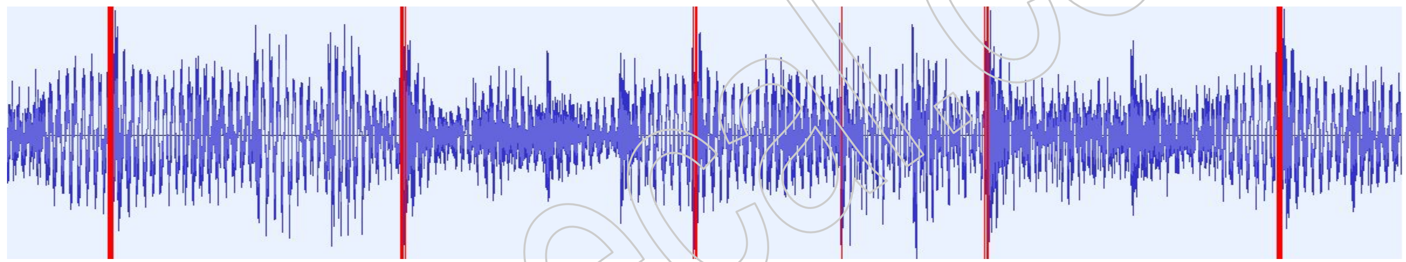
Chapter 2


1.33Hz = 80bpm
×10^4
7
6
5
4
3
2
1
0
Magnitude
0.5
1
1.5
2
2.5
3
Frequency (Hz)
Leader
Follower

Chapter 2

Data processing:

Music beats
High pass filter on the clave instrument allows clip detection



Beat 1 Beat 3 Beat 5 Beat 7 Beat 1

For each 520 sequences

For each time window of 8 beats

520 Dance sequences:
- 2 dance sequence type
- 26 couple
- 10 songs

3 Global features measurements:
- μ_9
- μ_{10}
- μ_{17}

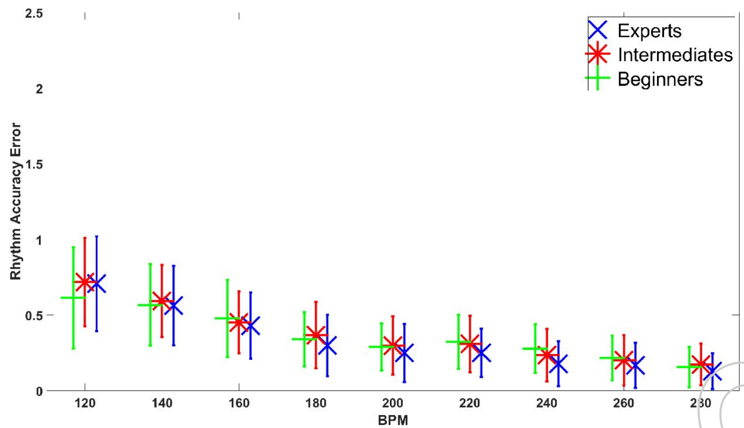
26 local feature measurements:
- $\mu_{1....29}$

+ Normalization

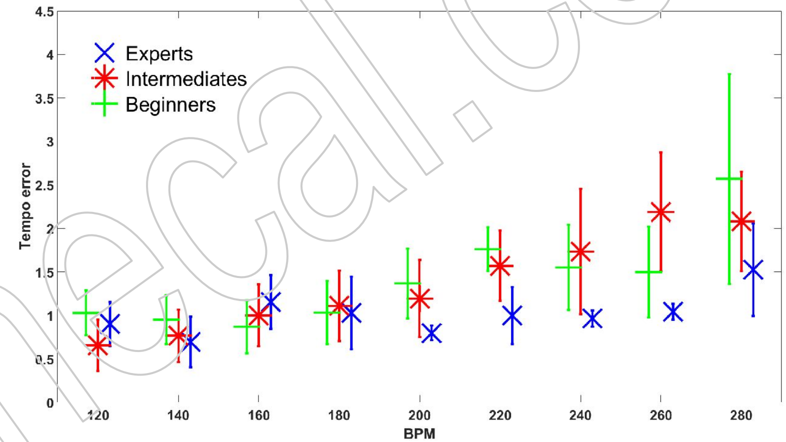
Data processing

Chapter 2

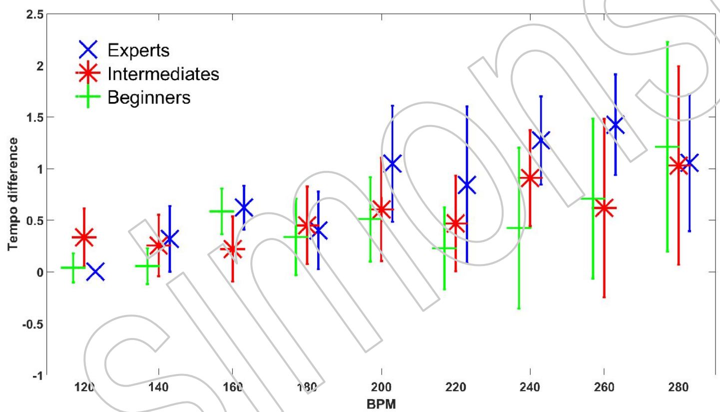
Tempo analysis:



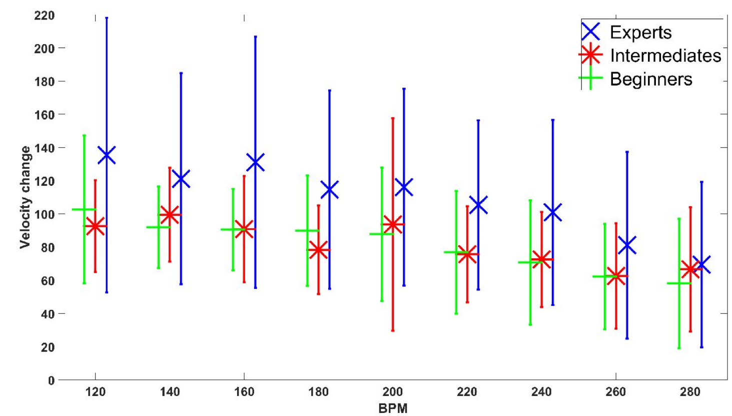
Rhythm



Average tempo



Average tempo difference

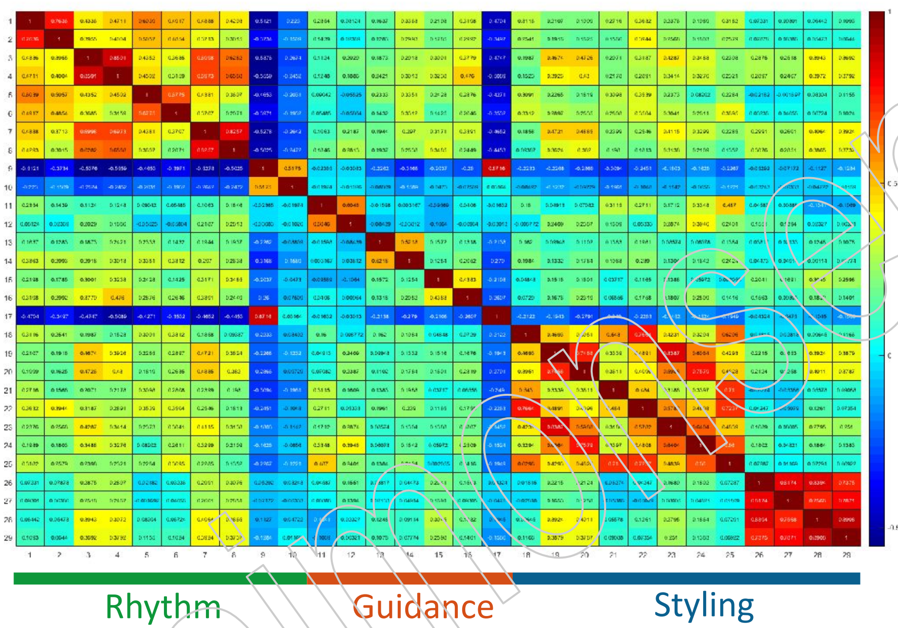


Net velocity

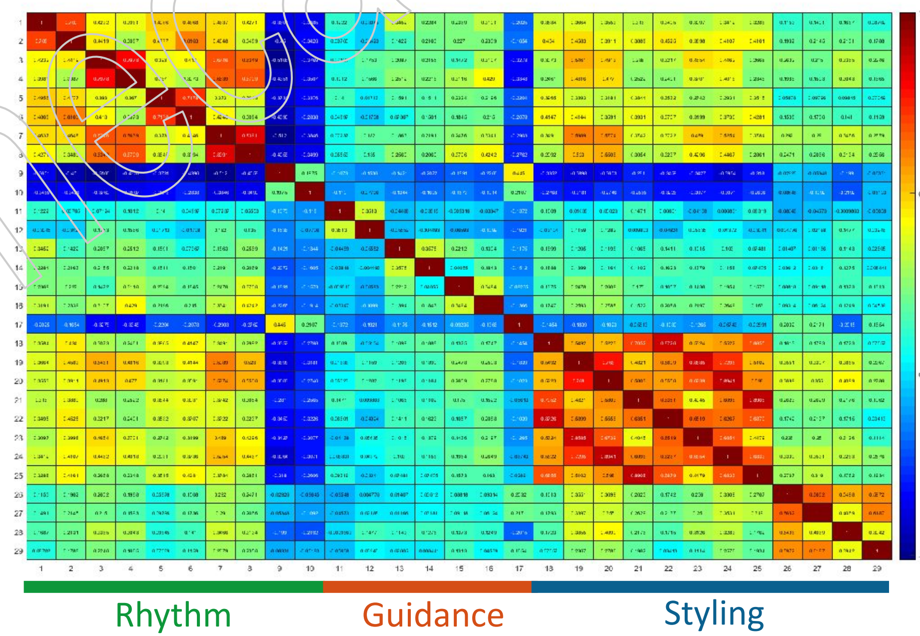
Chapter 2

Auto-Correlation:

High correlation = homogeneous values



Experts



Beginners

Chapter 2

Classification:

Extracted MMF from all data
5000 vector of 29 values as input /seq.

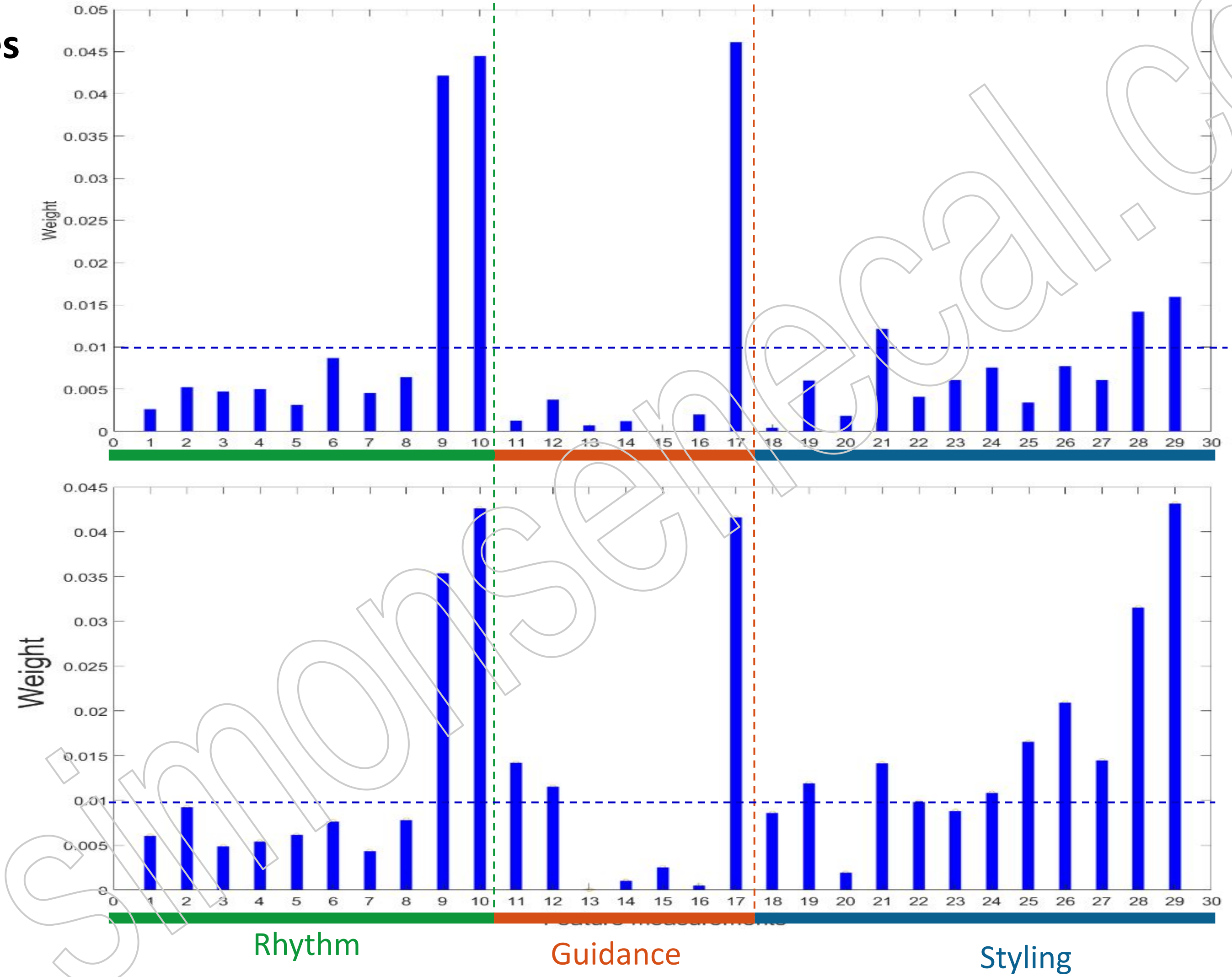
Three level classification (beginner – intermediate – experts)

	K-Nearest Neighbour			Support Vector Machine			Random Forest		
Seq.	*R*	*P*	*A*	*R*	*P*	*A*	*R*	*P*	*A*
Basic	76.10	78.07	77.54	80.12	81.91	80.10	91.26	87.48	**90.04**
Impro	69.13	70.09	70.02	65.75	64.29	65.12	83.75	84.63	**85.30**

Recall (R), Precision (P) , Accuracy (A)

Chapter 2

Features weight:



Basic steps

Improvisation

Summary & conclusion:

Motion corresponds to the **modelling**

Rhythm is more accurate and stable at **high dance speed**.

There is still some **difference** between the Leader and Follower for the Experts

Experts tends to **cover more space** and put more energy, with variations

Hands motion is more homogeneous for Experts.

90% accuracy to classify on Basic step sequence

Average tempo seems the **most reliable** to classify

Styling elements, especially **hand movements** are also very important

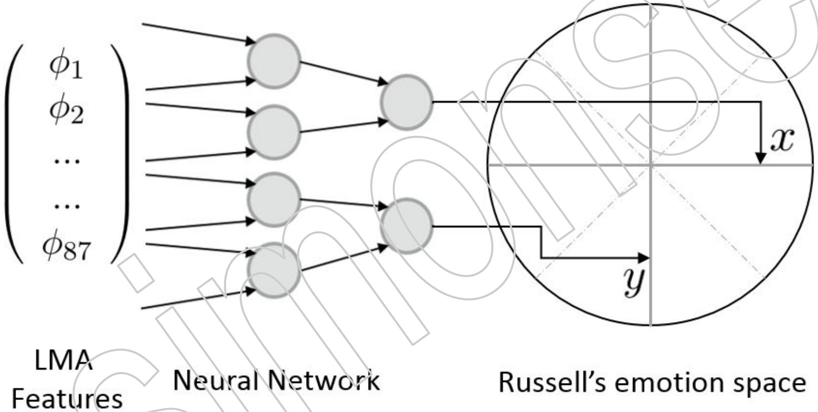
=> MMF shows to have potential to describe dance motion in terms of the dance skills

Chapitre 3:
Preliminary study on Laban motion analysis

Chapter 3

Laban Motion Analysis:
Expressive motion case study

Test of the ability of the **LMA features** to classify motion from **emotional** theater improvisation into emotional space.



Motion **database** of 12 actors performing 8 emotion in improvised matter.

Recording by **Kinect**.

Classification by **Neural network**.

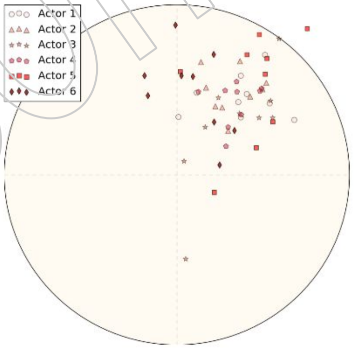
Motion analysis: Laban motion analysis (LMA)

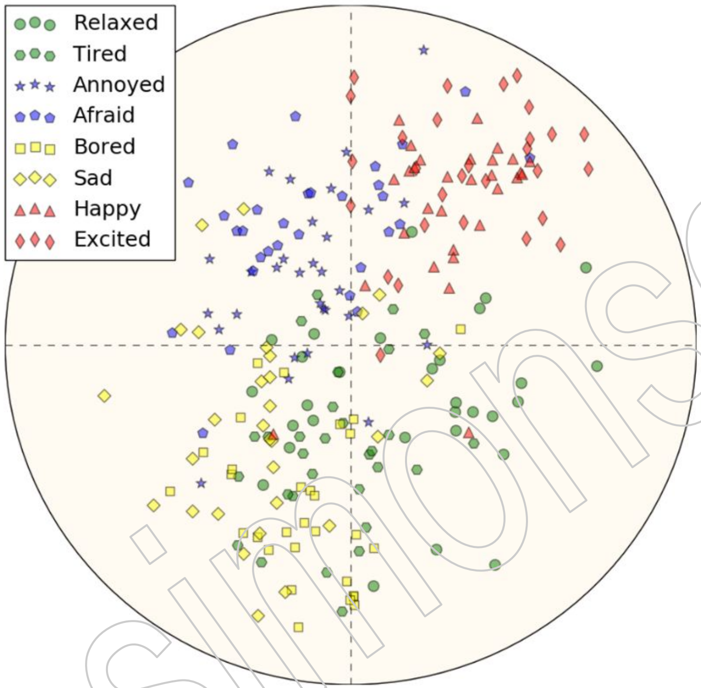
Use of LMA from distances among the different body joints, kinematics and geometry.

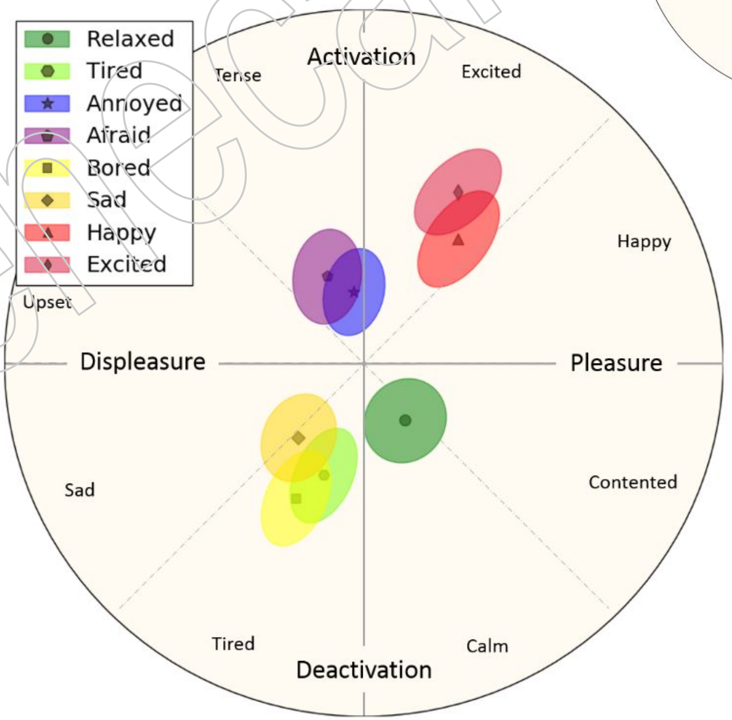
	Features		Measurements			
	f^i	Description	f^i_{max}	f^i_{min}	f^i_{σ}	f^i_{μ}
Body	f^1	Feet-hip distance	ϕ_1	ϕ_2	ϕ_3	ϕ_4
	f^2	Hands-shoulder distance	ϕ_5	ϕ_6	ϕ_7	ϕ_8
	f^3	Hands distance	ϕ_9	ϕ_{10}	ϕ_{11}	ϕ_{12}
	f^4	Hands-head distance	ϕ_{13}	ϕ_{14}	ϕ_{15}	ϕ_{16}
	f^5	Hands-hip distance	ϕ_{17}	ϕ_{18}	ϕ_{19}	ϕ_{20}
	f^6	Hip-ground distance	ϕ_{21}	ϕ_{22}	ϕ_{23}	ϕ_{24}
	f^7	Hip-ground minus feet-hip	ϕ_{25}	ϕ_{26}	ϕ_{27}	ϕ_{28}
	f^8	Centroid-ground distance	ϕ_{29}	ϕ_{30}	ϕ_{31}	ϕ_{32}
	f^9	Gait size	ϕ_{33}	ϕ_{34}	ϕ_{35}	ϕ_{36}
Effort	f^{10}	Head orientation	ϕ_{37}		ϕ_{38}	ϕ_{39}
	f^{11}	Deceleration peaks				ϕ_{40}
	f^{12}	Pelvis velocity	ϕ_{41}		ϕ_{42}	ϕ_{43}
	f^{13}	Hands velocity	ϕ_{44}		ϕ_{45}	ϕ_{46}
	f^{14}	Feet velocity	ϕ_{47}		ϕ_{48}	ϕ_{49}
	f^{15}	Pelvis acceleration	ϕ_{50}		ϕ_{51}	
	f^{16}	Hands acceleration	ϕ_{52}		ϕ_{53}	
	f^{17}	Feet acceleration	ϕ_{54}		ϕ_{55}	
	f^{18}	Jerk	ϕ_{56}		ϕ_{57}	
Shape	f^{19}	Volume (5 joints)	ϕ_{58}	ϕ_{59}	ϕ_{60}	ϕ_{61}
	f^{20}	Volume (upper body)	ϕ_{62}	ϕ_{63}	ϕ_{64}	ϕ_{65}
	f^{21}	Volume (lower body)	ϕ_{66}	ϕ_{67}	ϕ_{68}	ϕ_{69}
	f^{22}	Volume (left side)	ϕ_{70}	ϕ_{71}	ϕ_{72}	ϕ_{73}
	f^{23}	Volume (right side)	ϕ_{74}	ϕ_{75}	ϕ_{76}	ϕ_{77}
	f^{24}	Torso height	ϕ_{78}	ϕ_{79}	ϕ_{80}	ϕ_{81}
	f^{25}	Hands level				ϕ_{82}- ϕ_{84}
Space	f^{26}	Total distance				ϕ_{85}
	f^{27}	Total area				ϕ_{86}
	f^{28}	Total volume				ϕ_{87}

Case study result

Projection of the 87 LMA features onto 2D emotional space.



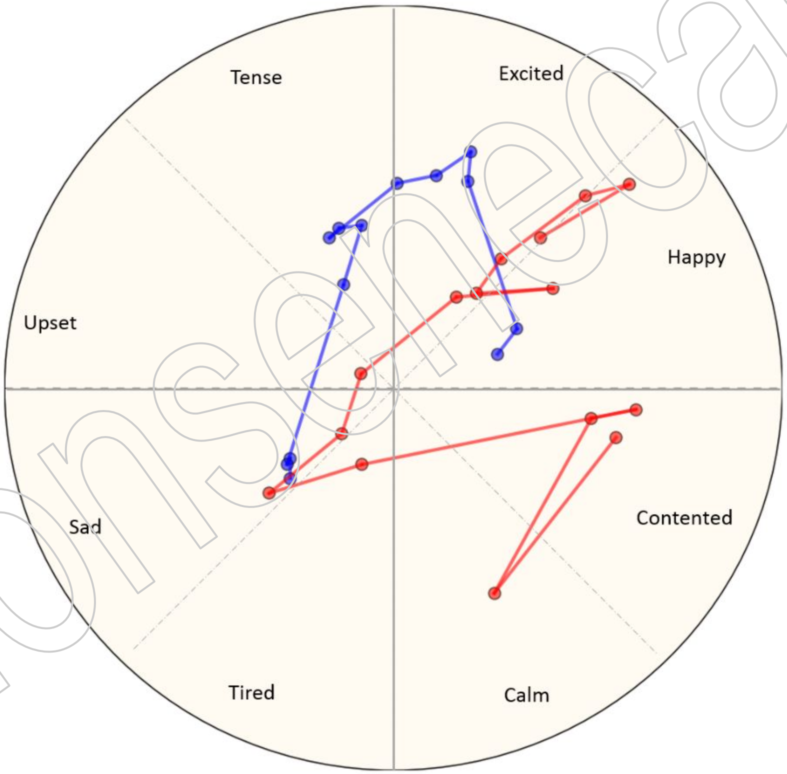




Chapter 3

Case study result

Special sequence of continuous change of emotional expression



Chapter 3:
Virtual reality salsa dance learning and motion analysis

Chapter 3

Virtual reality interactive dance learning system

Learning system:

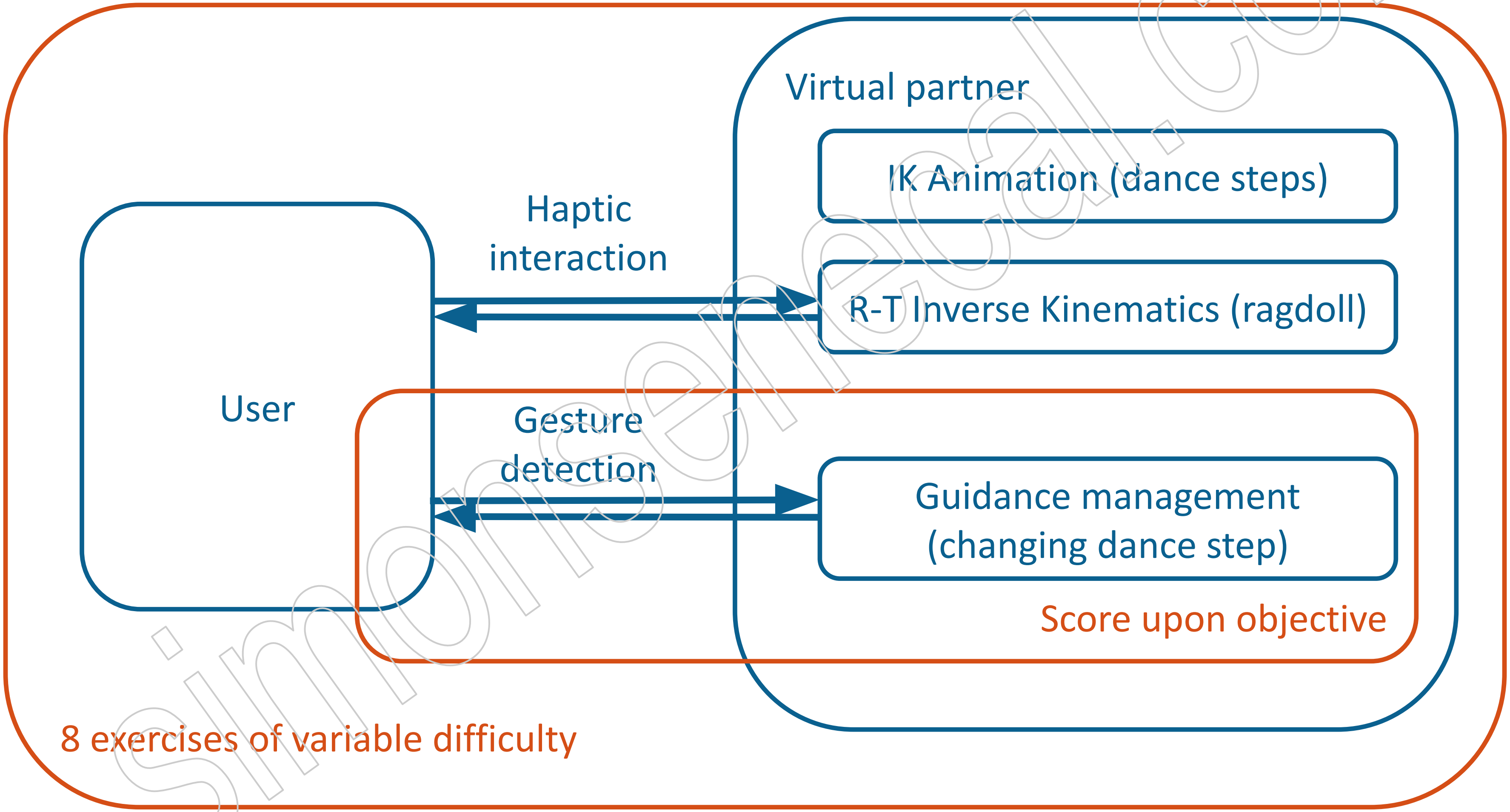
- Improvement of **dance skills**
- Performance **evaluation**

Simulation of Salsa dance:

- Salsa dance **motion**
- Hands to hands **interaction**
- Dance **sequences**

Chapter 3

Overview: Salsa simulator and Learning system



Chapter 3

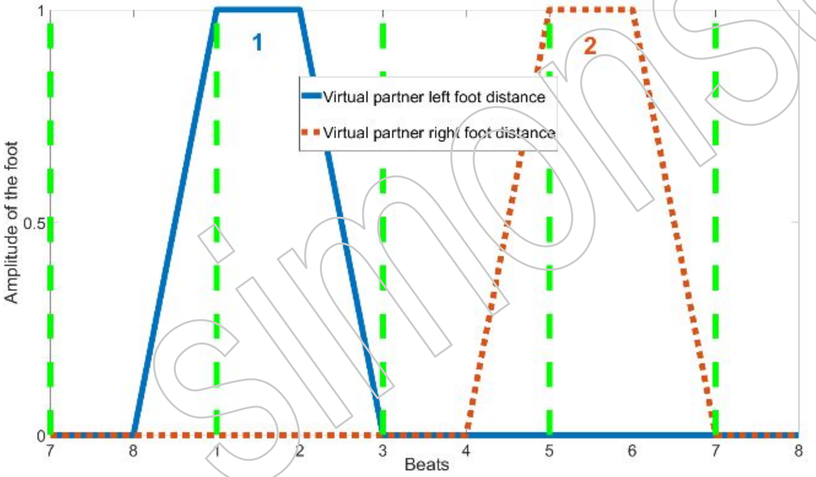
Virtual partner model and music synchronized dance animation

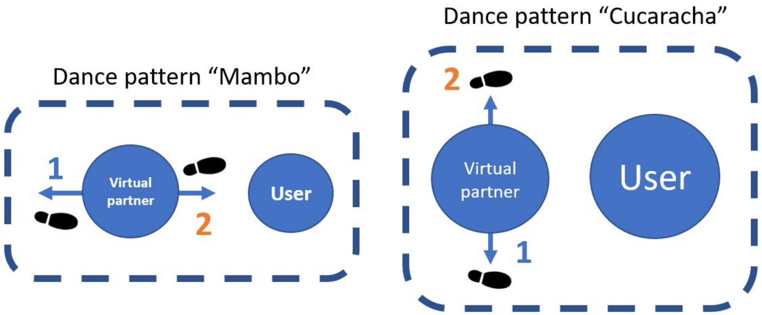
Realistic avatar

Motion **synchronize**d with IK rig

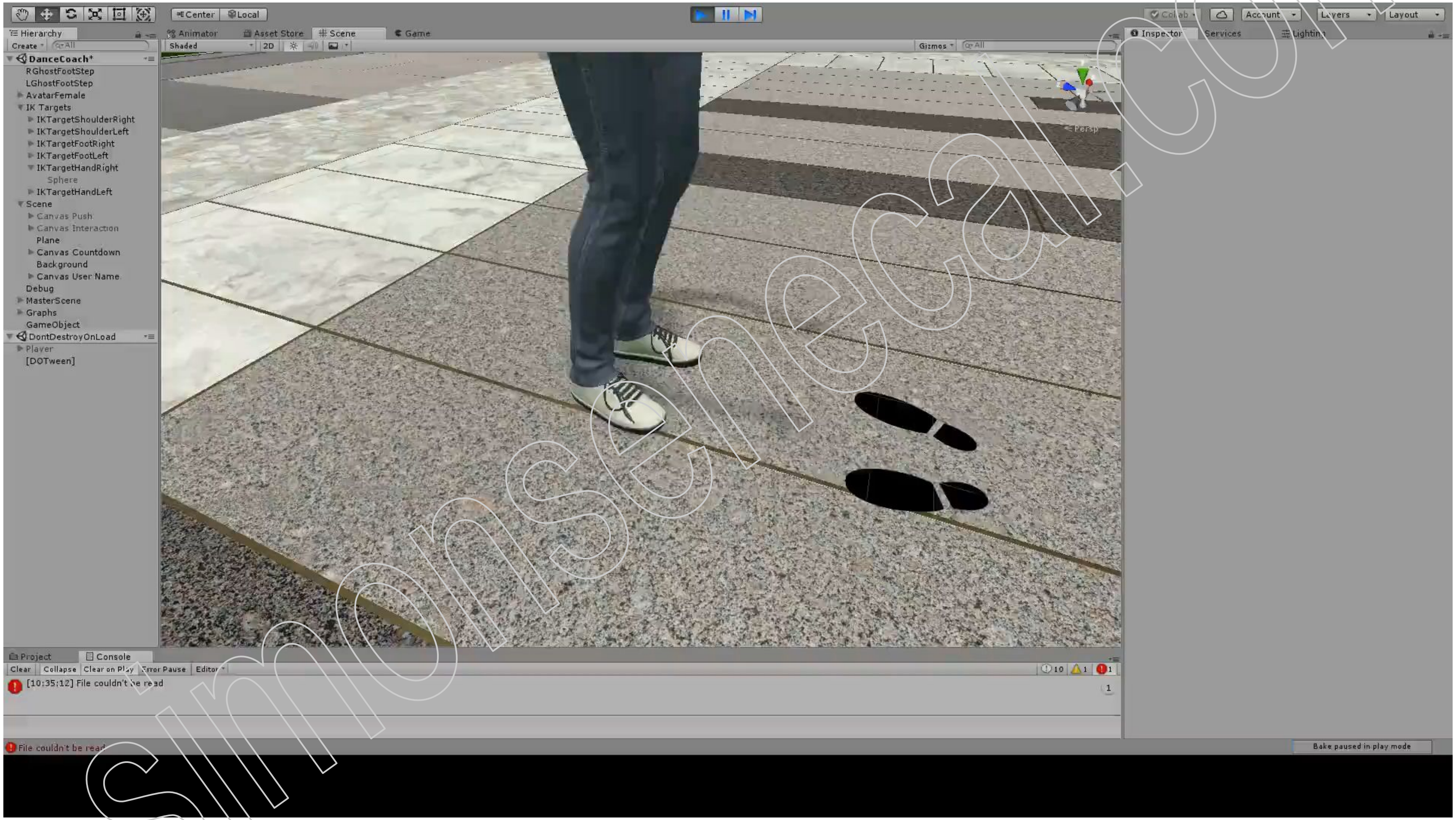
Root bone **moving** as the feet.

Period **proportional** to the music tempo





Chapter 3


Center
Local
Hierarchy
Animator
Asset Store
Scene
Game
Inspector
Services
Lighting
Account
Layers
Layout
Shaded
2D
Gizmos
DanceCoach*
RGhostFootStep
LGhostFootStep
AvatarFemale
IK Targets
IKTargetShoulderRight
IKTargetShoulderLeft
IKTargetFootRight
IKTargetFootLeft
IKTargetHandRight
Sphere
IKTargetHandLeft
Scene
Canvas Push
Canvas Interaction
Plane
Canvas Countdown
Background
Canvas User Name
Debug
MasterScene
Graphs
GameObject
DontDestroyOnLoad
Player
[DOTween]
Project
Console
Clear
Collapse
Clear on Play
Error Pause
Editor
[10:35:12] File couldn't be read
File couldn't be read
Bake paused in play mode

Chapter 3

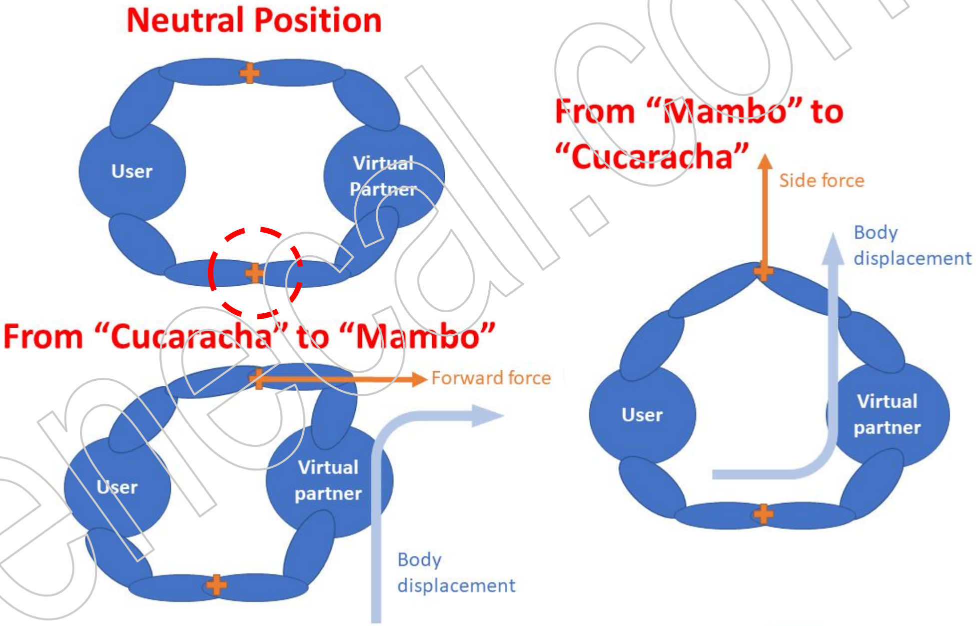
User interaction: guiding the virtual partner

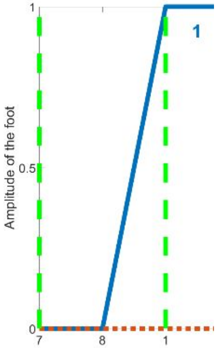
Hand to hands **snapping**

Neutral zone and **vibration**

Upper body **bends**

Transition **detection**: forces direction with dot product. (7->8 beat)





Chapter 3

Chapter 3

Chapter 3

Learning and gamification

Improving rhythm (**shadow steps**)

Two **simultaneous** dance tasks

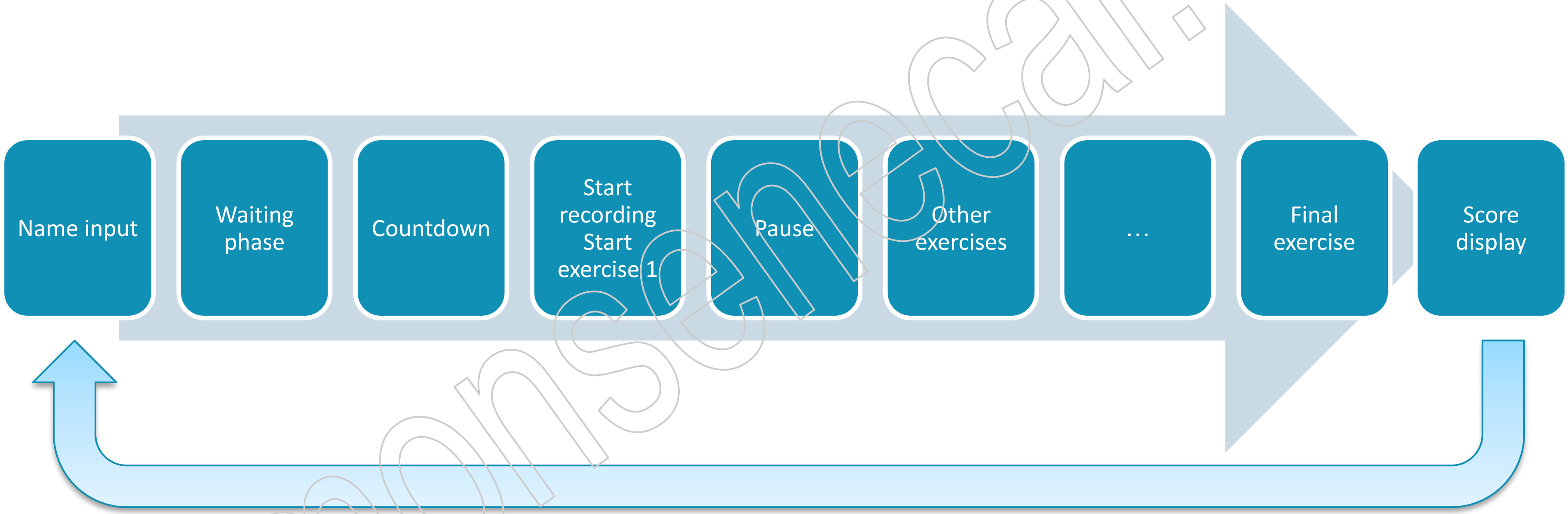
Repetition of the task possible on **songs** of regular length

Sequential exercises

Score at the end as reward

Chapter 3

Software design



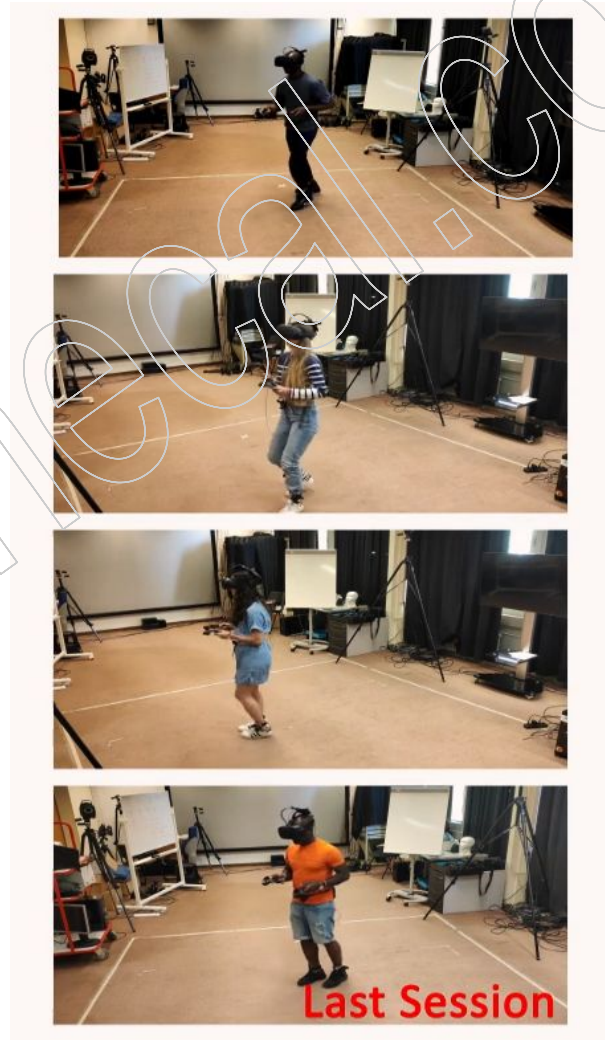
Chapter 3

Experiment: learning dance skills

- 20 non-dancers
- 20 regular dancers
- T1: Dance with the Virtual partner
- T2: Guidance transition every 16 beats
- 60s for each exercise
- HTC Vive VR set with 3 additional markers: 6-point skeleton at 100Hz
- All motion data recorded

Exercises	Tempo of the music (bpm)	Remarks
Exo 1	180	Serve as tutorial for people to get into it
Exo 2	180	Same tempo
Exo 3	180	Same tempo
Exo 4	160	Tempo slower
Exo 5	200	Tempo faster
Exo 6	140	Slowest tempo, easiest for non dancer
Exo 7	220	Faster tempo, very difficult for non dancer
Exo 8	180	Back to the initial tempo

Chapter 3



Chapter 3

Data processing

Motion data

User 1
exo 1
-
exo 8

User 2
exo 1
-
exo 8

…

LMA and MMF extraction →

LMA / MMF separately

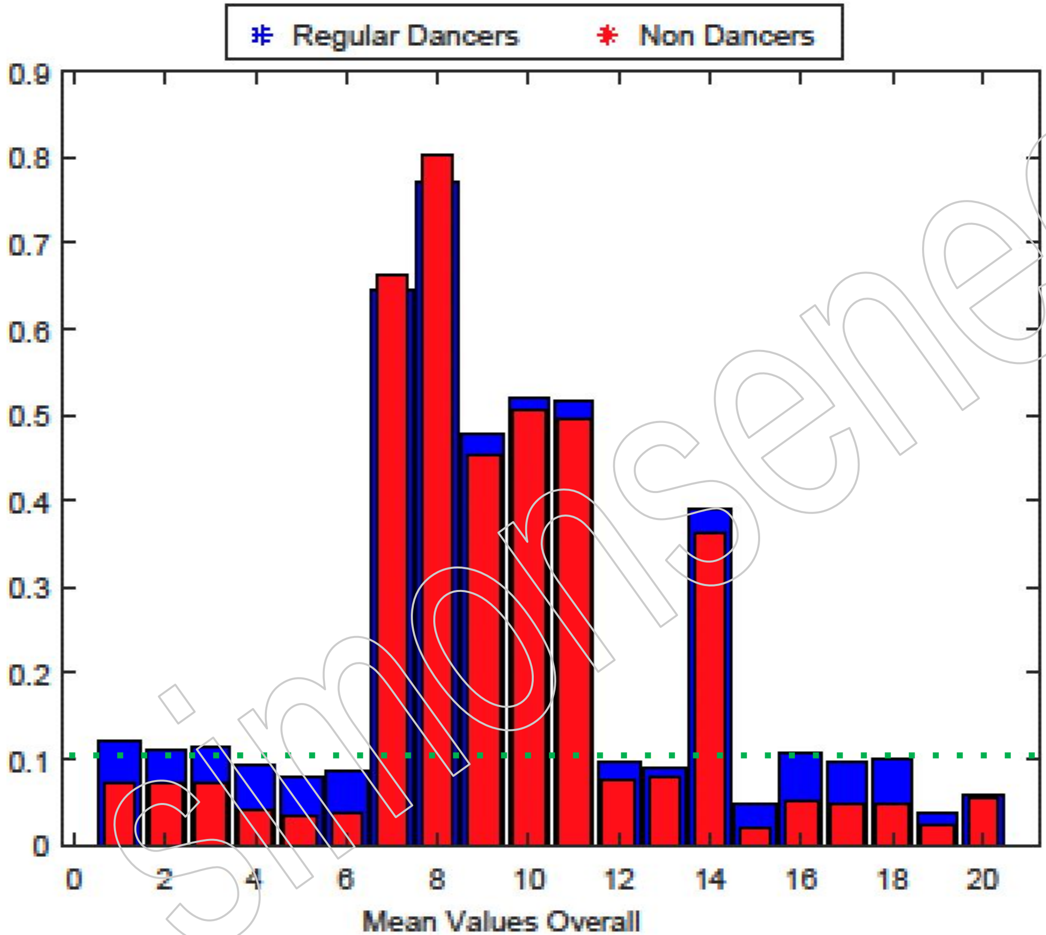
- Per feature average comparison per category
- Per feature before / after training comparison per category
- Per feature STD comparison per category
- 2D projection / cluster analysis

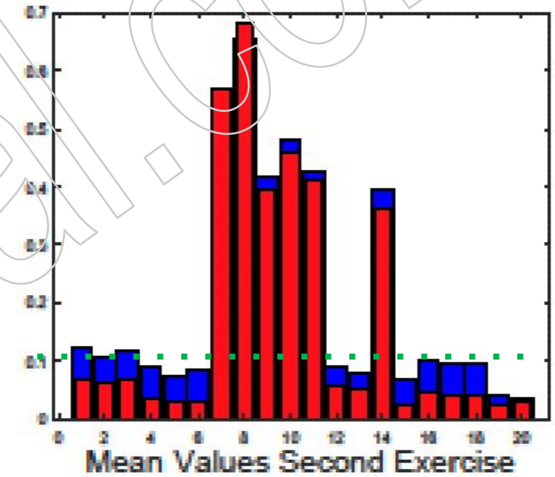
Motion analysis: Laban motion analysis (LMA)

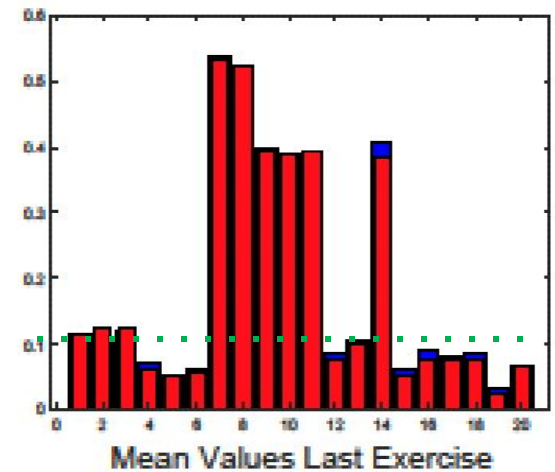
20 LMA features from previous chapter

A/A	LMA	Description
1.	ϕ_{11}	Left hand-shoulder distance (std)
2.	ϕ_{12}	Left hand-shoulder distance (mean)
3.	ϕ_{15}	Right hand-shoulder distance (std)
4.	ϕ_{16}	Right hand-shoulder distance (mean)
5.	ϕ_{19}	Hands distance (std)
6.	ϕ_{20}	Hands distance (mean)
7.	ϕ_{47}	Gait size (std)
8.	ϕ_{57}	Left hand velocity (max)
9.	ϕ_{59}	Left hand velocity (mean)
10.	ϕ_{60}	Right hand velocity (max)
11.	ϕ_{62}	Right hand velocity (mean)
12.	ϕ_{65}	Left foot velocity (mean)
13.	ϕ_{68}	Right foot velocity (mean)
14.	ϕ_{69}	Pelvis acceleration (max)
15.	ϕ_{71}	Left hand acceleration (max)
16.	ϕ_{73}	Right hand acceleration (max)
17.	ϕ_{75}	Left foot acceleration (max)
18.	ϕ_{77}	Right foot acceleration (max)
19.	ϕ_{104}	Torso height (mean)
20.	ϕ_{114}	Cumulative distribution (mean)

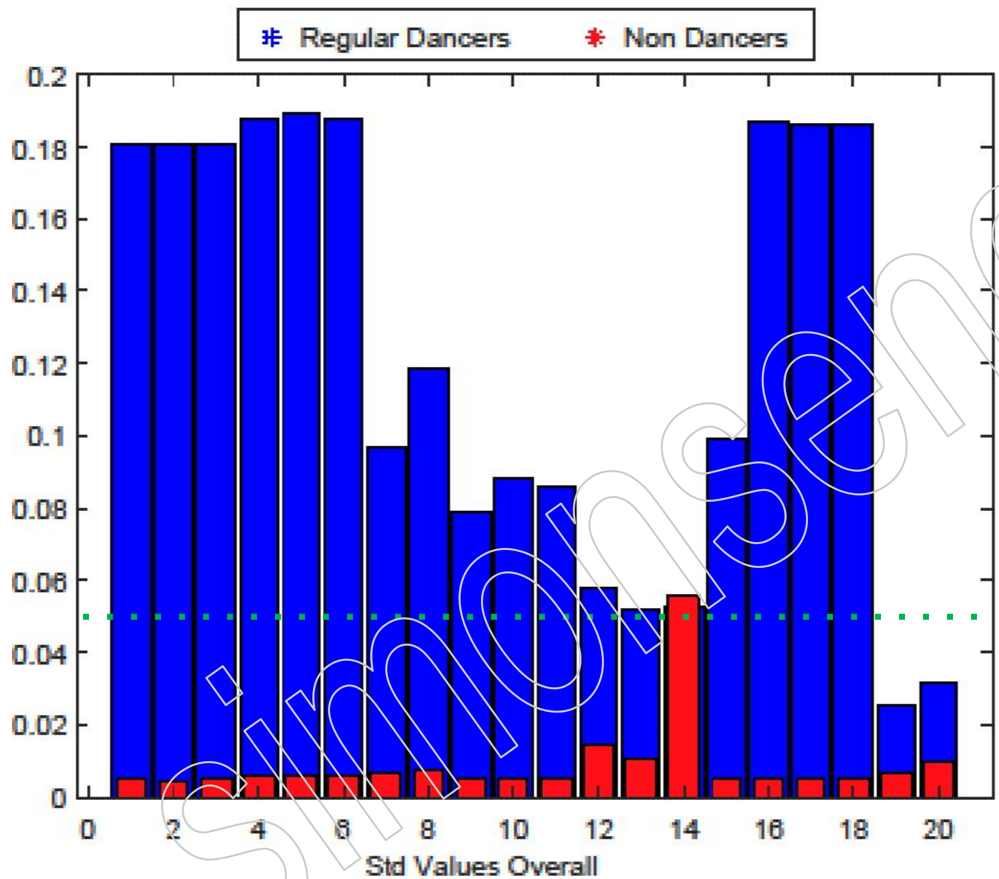
Average value

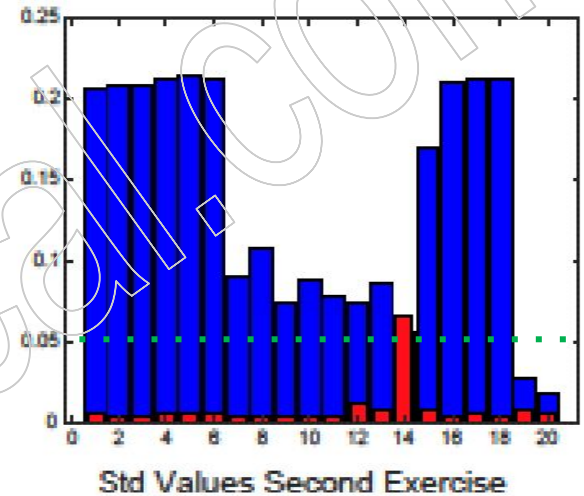


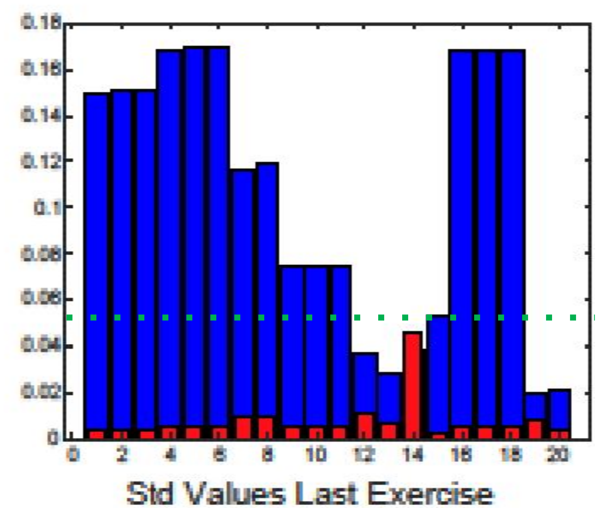




Standard deviation

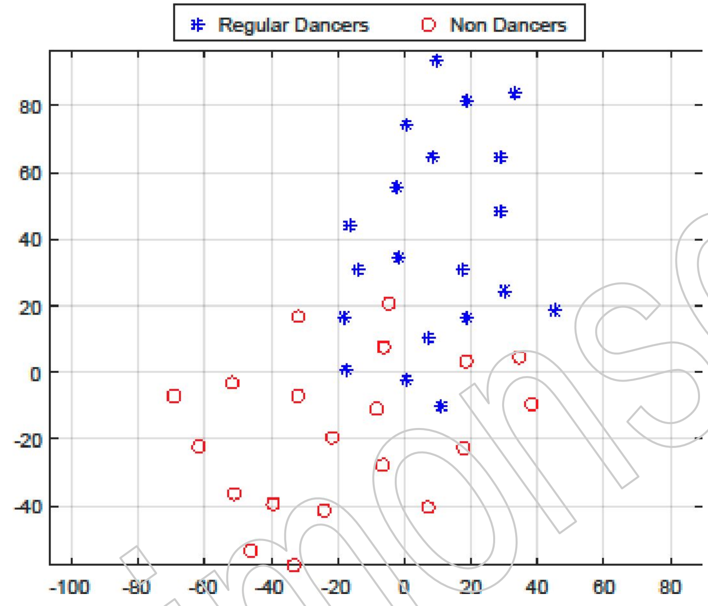


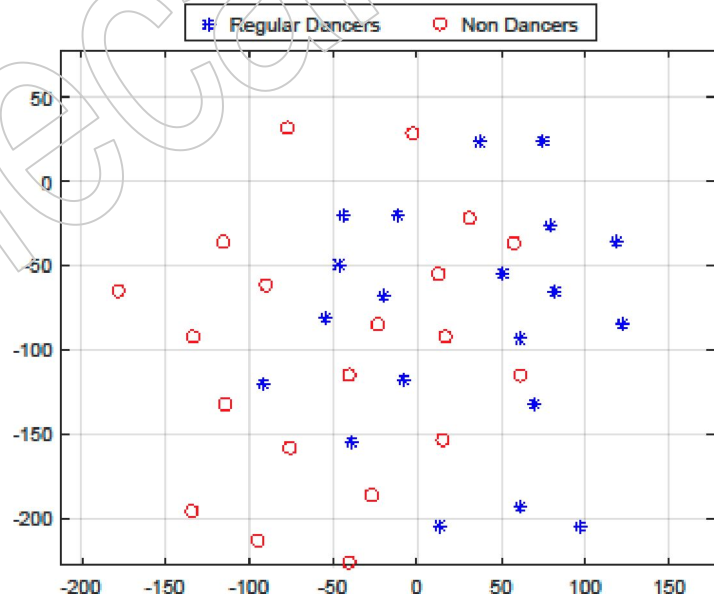




2D projection

Comparison before and after training



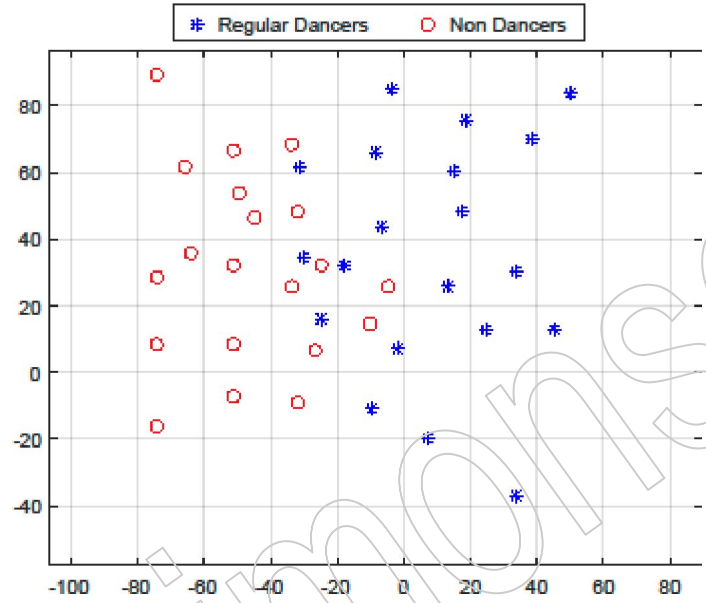


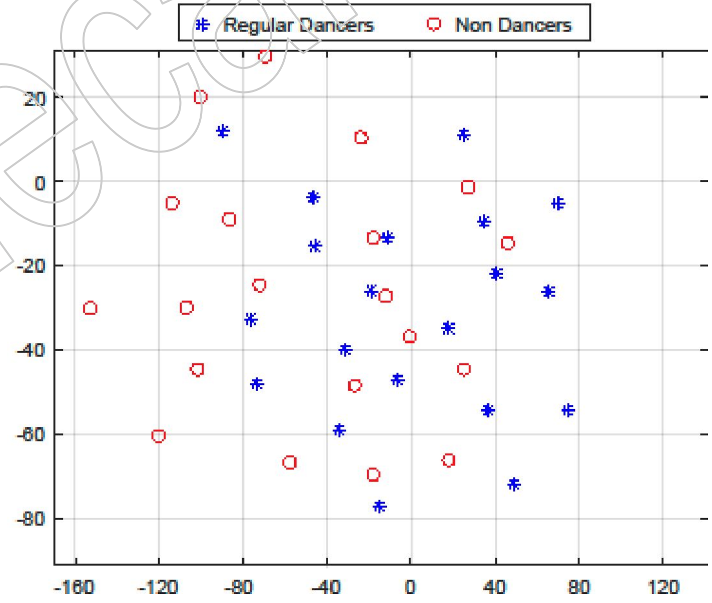
Before training: distribution is clearly separated

After training: distribution is mixed

2D projection: Using motion signature

Comparison before and after training





Before training: distribution is clearly separated

After training: distribution is mixed

Summary

Regular dancers have bigger **hands distances** and hands/feet **acceleration** in average.

Regular dancers shows bigger **variation** of their features, except for Pelvis acceleration.

Values **converged** towards the Regular dancers' ones. Only Pelvis acceleration doesn't change much.

Variations of features from regular dancers is **decreasing** after training but there is **still** a big difference with the non dancers.

=> Non dancers changed their LMA features towards Regular dancers

Chapter 3

Introduction | SoA | Chapter 1 | Chapter 2 | **Chapter 3** | Conclusion

Motion analysis: Musical motion features (MMF)

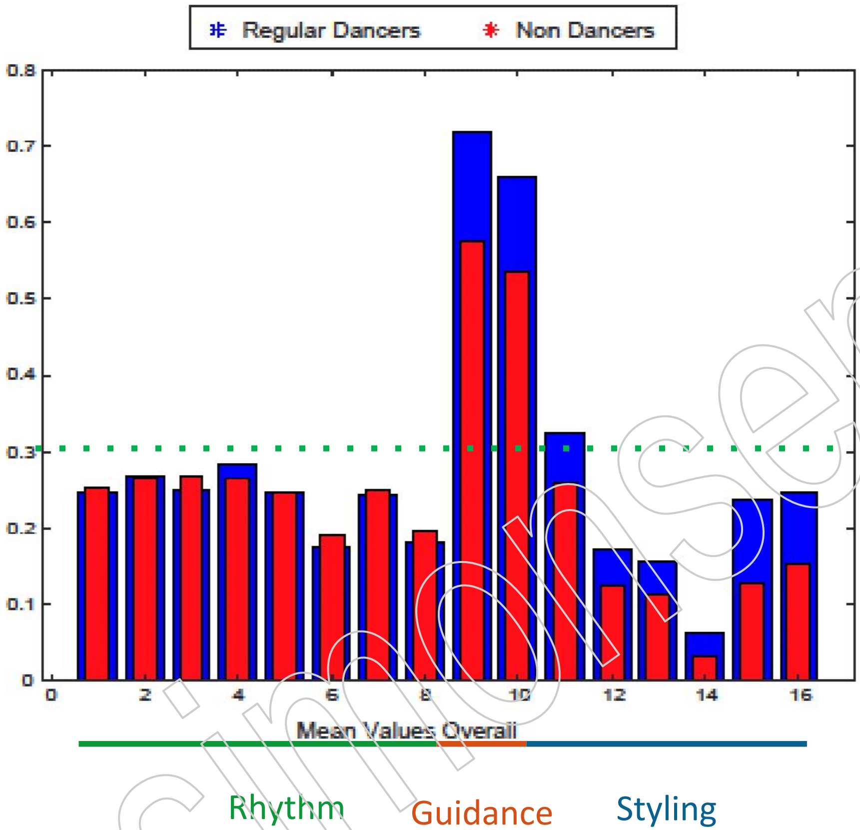
16 MMF from previous chapter

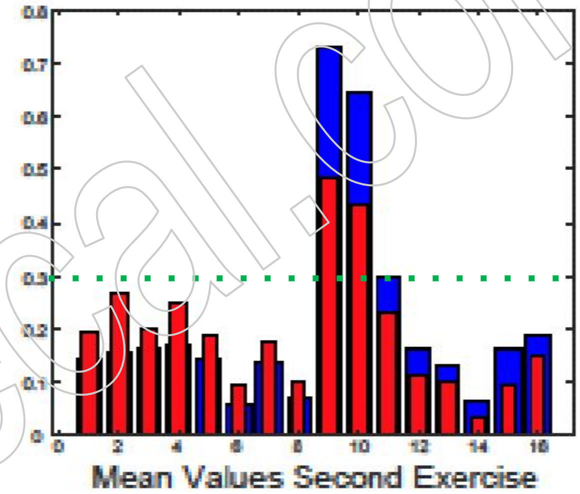
Table 5.2 – Subset of the Musical Motion Features in our case of Virtual Reality

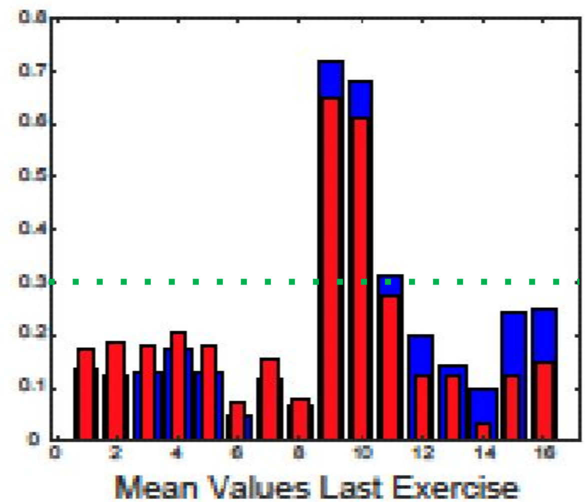
		MMF	Measurements details
Rhythm	Step Accuracy (Rhythm)	μ_1	Temporal accuracy of left foot over beat 1
		μ_2	Temporal accuracy of left foot over beat 3
		μ_3	Temporal accuracy of right foot over beat 5
		μ_4	Temporal accuracy of right foot over beat 7
	Rhythm difference between partners (Rhythm)	μ_5	Temporal difference user left foot /VP right foot over beat 1
		μ_6	Temporal difference user left foot /VP right foot over beat 3
		μ_7	Temporal difference user right foot /VP left foot over beat 5
		μ_8	Temporal difference user right foot /VP left foot over beat 7
Guidance	Foot Correlation (Guidance)	μ_9	Correlation coefficient beat 1 to 3 user left foot / VP right foot
		μ_{10}	Correlation coefficient beat 5 to 7 user right foot /VP left foot
Style	Area (Styling)	μ_{11}	Displacement of the left foot over 8 beats
		μ_{12}	Displacement of the right foot over 8 beats
		μ_{13}	Net velocity change of the left foot over 8 beats
		μ_{14}	Net velocity change of the right foot over 8 beats
	Hands Movements (Styling)	μ_{15}	Mean distance left hand to hips over 8 beats
		μ_{16}	Mean distance right hand to hips over 8 beats

Chapter 3

Average value

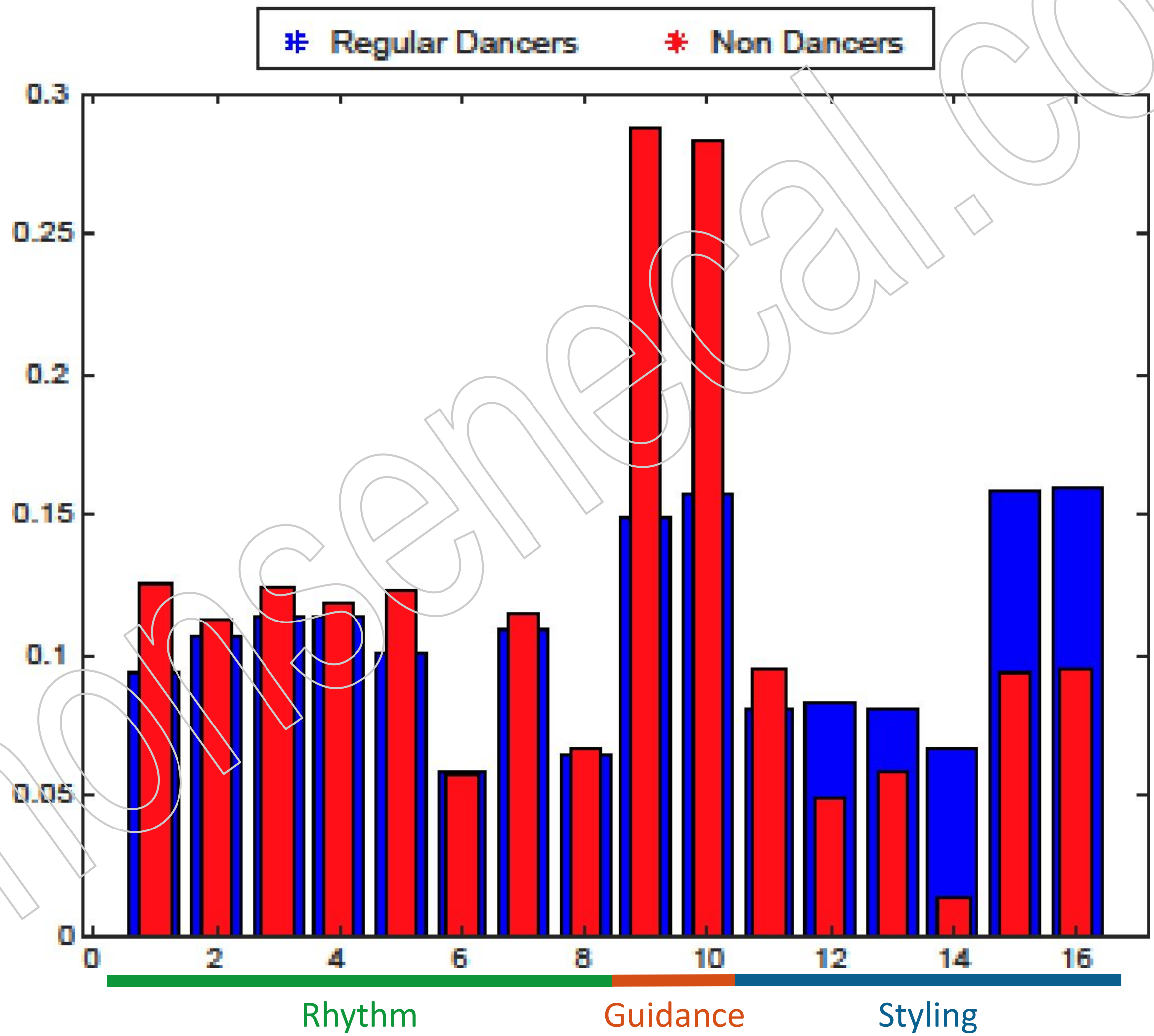






Chapter 3

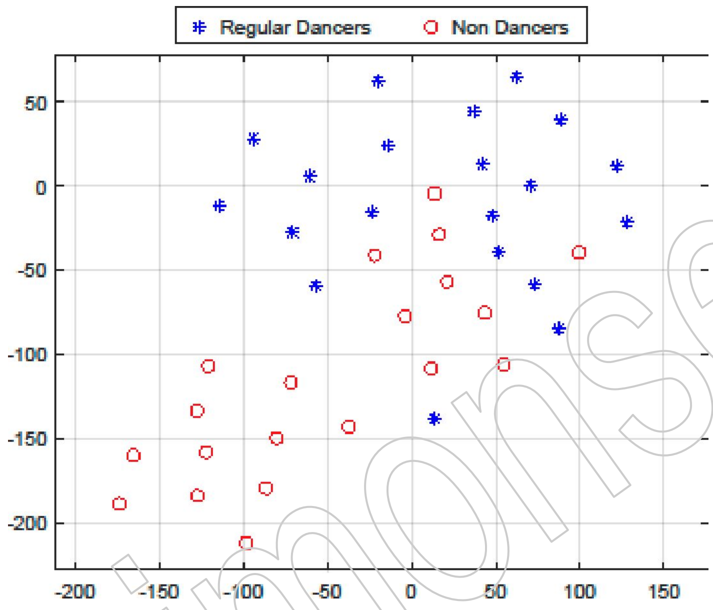
Standard deviation



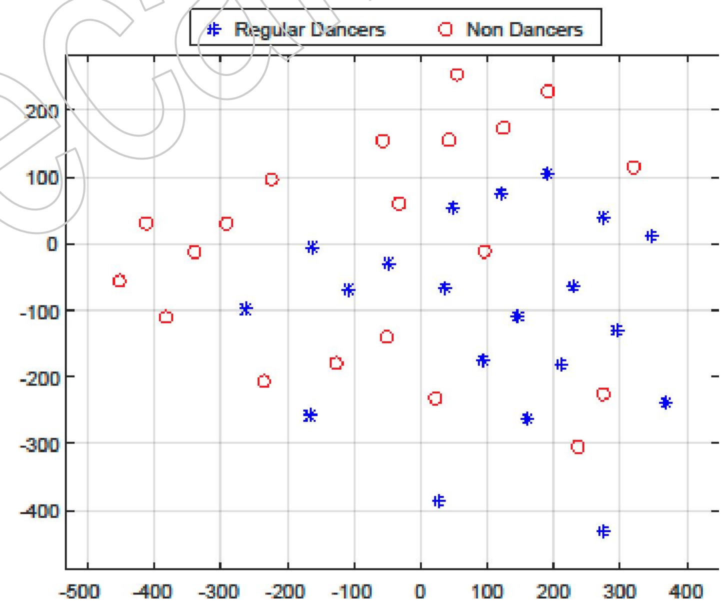
Chapter 3

2D projection / cluster analysis

Comparison before and after training



Before training: distribution is clearly separated



After training: distribution is mixed

Summary

Regular dancers have a bigger **foot correlation**, and higher value and variation of **styling** elements.

Non dancers shows big **variation** of foot correlation.

Regular dancers have almost the **same values** after training.

Normal dancers **converged** globally towards the regular dancers' values: they decreased the rhythm error and increased **drastically** their foot correlation.

=> Non dancer improved their dance skills

MMF allows to have more meaning about what skills are improved

Conclusion

Contributions:

1.We proposed a **set of motion features (MMF)** able to evaluate a salsa performance.

- Able to **characterize** 3D motion data from two dancers + music
- **Interface** between motion data and dance skills

-> Limitations: Some of the features are **more important** than other
Focused on the foot motion, more **rhythm** than guidance

2.We designed a **dance learning system** with exercises that improves the dance skills of users

- Two **simultaneous** dance tasks in **synchronization** with music
- Evaluation with **motion analysis** (MMF / LMA)

-> Limitations: Some of the features are more important than other
Focused on the foot motion, more rhythm than guidance
The categories of dancer per experience is difficult to define
Non dancers trained only 500s in total

Conclusion

3.We proposed a dance **animation method** based on IK synchronized with music tempo.

-> Limitations: The animation is still very "robotic" looking.
The upper part of the body is not animated

4.We proposed natural **dance interaction for VR** based on hands snapping and IK deformation

-> Limitations: We cannot induce translation to the VP, nor have speed interaction.

5.We proposed a **guidance simulation method** to have natural dance pattern transition

-> Limitations: The gesture detection based on pulling/pushing the VP needs the user to exaggerate his/her movements compare to a regular one

6.Six dance skills **identified** important for learning.

-> Limitations: Only validated by Salsa experts

Conclusion

Introduction | SoA | Chapter 1 | Chapter 2 | Chapter 3 | **Conclusion**

Future work:

Try real-time motion analysis to provide feedback in a fast way

Establish a longer study and ask expert to rate the improvement

Refine the motion features categories and add other relevant measurements

Look for full body animation compatible with the interaction system

Research a way to induce translation and turns to the VP, as well as speed interaction

Identify the right gesture or motion that passes the information of dance transition

Search dance skills from other style of partner dance.

Investigate other dance skills (Sharing, musicality, fluidity)

Thank you very much for your attention.

Publications:

- **S. Senecal**, N. Nijdam, A. Aristidou and N. Magnenat-Thalmann, "Salsa dance learning evaluation and motion analysis in gamified virtual reality environment [Accepted]", **Multimedia tools and application, Springer, 2020.**
- **S. Senecal**, N. Nijdam, and N. Magnenat-Thalmann, "Classification of salsa dance level using music and interaction-based motion features", **GRAPP 2019 -** International conference on Computer Graphics Theory and Applications, 2019.
- **S. Senecal**, N. Nijdam, and N. Magnenat-Thalmann, "Motion analysis, indexing and classification of salsa dance using music-related motion features", ACM conference of motion in games, **MIG, 2018.**
- **S. Senecal**, L. Cuel, A. Aristidou, and N. Magnenat-Thalmann, "Continuous body emotion recognition system during theater performances", **Computer Animation and Virtual Worlds, 2016**.

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Active@Home, AAL

Virtual Multimodal Mueum

MIRALab members

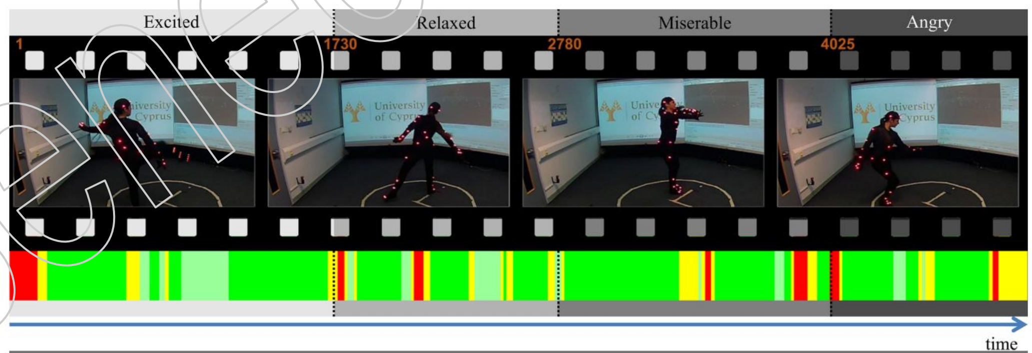
Family and friends

Literature review

f_s	Description	Measurement max	min	mean	std	#
f_1	Feet–hip distance	ϕ_1	ϕ_2	ϕ_3	ϕ_4	
f_2	Hands–shoulder distance	ϕ_5	ϕ_6	ϕ_7	ϕ_8	
f_3	Hands distance	ϕ_9	ϕ_{10}	ϕ_{11}	ϕ_{12}	
f_4	Hands–head distance	ϕ_{13}	ϕ_{14}	ϕ_{15}	ϕ_{16}	
f_5	Pelvis height	ϕ_{17}	ϕ_{18}	ϕ_{19}	ϕ_{20}	
f_6	Hip-ground minus feet-hip	ϕ_{21}	ϕ_{21}	ϕ_{23}	ϕ_{24}	
f_7	Centroid height	ϕ_{25}	ϕ_{26}	ϕ_{27}	ϕ_{28}	
f_8	Centroid–pelvis distance	ϕ_{29}	ϕ_{30}	ϕ_{31}	ϕ_{32}	
f_9	Gait size	ϕ_{33}	ϕ_{34}	ϕ_{35}	ϕ_{36}	
f_{10}	Head orientation	ϕ_{37}	ϕ_{38}	ϕ_{39}		
f_{11}	Deceleration peaks					ϕ_{40}
f_{12}	Hip velocity	ϕ_{41}	ϕ_{42}		ϕ_{43}	
f_{13}	Hands velocity	ϕ_{44}	ϕ_{45}		ϕ_{46}	
f_{14}	Feet velocity	ϕ_{47}	ϕ_{48}		ϕ_{49}	
f_{15}	Hip acceleration	ϕ_{50}			ϕ_{51}	
f_{16}	Hands acceleration	ϕ_{52}			ϕ_{53}	
f_{17}	Feet acceleration	ϕ_{54}			ϕ_{55}	
f_{18}	Jerk	ϕ_{56}			ϕ_{57}	
f_{19}	Volume	ϕ_{58}	ϕ_{59}	ϕ_{60}	ϕ_{61}	
f_{20}	Volume (upper body)	ϕ_{62}	ϕ_{63}	ϕ_{64}	ϕ_{65}	
f_{21}	Volume (lower body)	ϕ_{66}	ϕ_{67}	ϕ_{68}	ϕ_{69}	
f_{22}	Volume (left side)	ϕ_{70}	ϕ_{71}	ϕ_{72}	ϕ_{73}	
f_{23}	Volume (right side)	ϕ_{74}	ϕ_{75}	ϕ_{76}	ϕ_{77}	
f_{24}	Torso height	ϕ_{78}	ϕ_{79}	ϕ_{80}	ϕ_{81}	
f_{25}	Hands level					ϕ_{82}–ϕ_{84}
f_{26}	Total distance					ϕ_{85}
f_{27}	Total area					ϕ_{86}

Contemporary dance emotion expression recognition

- Using 86 LMA-inspired features
- Recognition of 2-dim emotions (8 emotions)
- Learning using random forest and SVM on a database



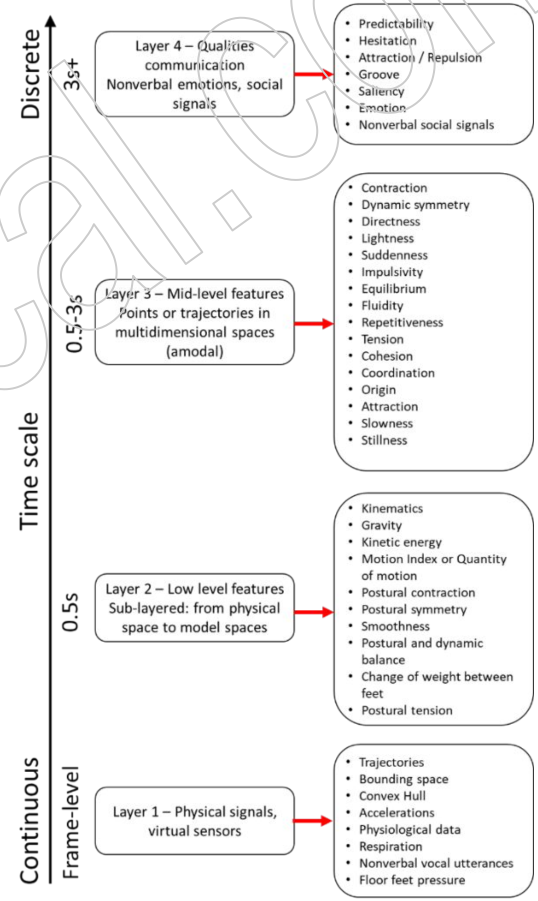
Recognition rate between 80 and 90% on the database

- Aristidou, A., Charalambous, P., & Chrysanthou, Y. (2015). Emotion Analysis and Classification: Understanding the Performers' Emotions Using the LMA Entities. *Computer Graphics Forum*
- Aristidou, A., & Chrysanthou, Y. (2013). Motion indexing of different emotional states using LMA components. *SIGGRAPH Asia 2013 Technical Briefs on - SA '13*

Literature review

DANCE framework:

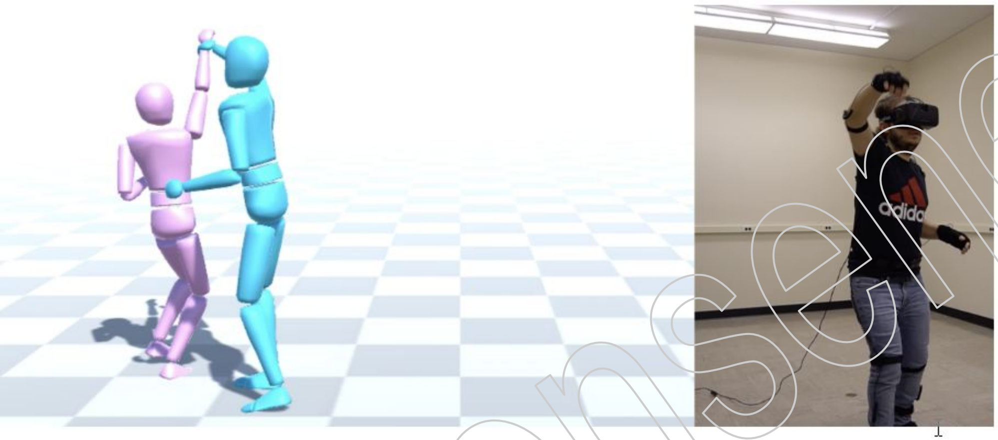
- Structure the motion from an external observer perspective.
- Developed to characterize and classify expressive motion
- Low level is continuous and High level is discreet
- Several papers of the EU project use part of this framework



Camurri, A., Volpe, G., Piana, S., Mancini, M., Niewiadomski, R., Ferrari, N., & Canepa, C. (2016). The Dancer in the Eye. *Proceedings of the 3rd International Symposium on Movement and Computing - MOCO '16*, 1–7.

Literature review

Virtual reality interactive Salsa dance

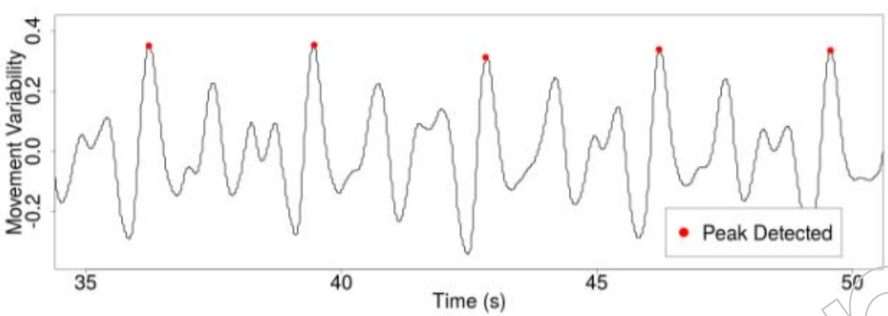


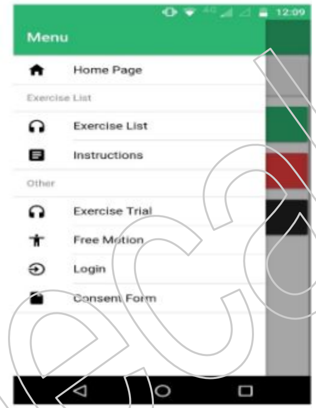
- HMM motion synthesis based on postures sequences
- 7-point Likert scale to evaluate the system:
- Better results for: Hand contact (M= 6.73, SD= 1.09)

Mousas, C. (2018). Performance-Driven Dance Motion Control of a Virtual Partner Character. *25th IEEE Conference on Virtual Reality and 3D User Interfaces, VR 2018 - Proceedings*, 57–64.

Literature review

Forro learning application





- App that follows student's progress
- Rhythm constituency detected with the peak of motion

Student ID	# of Practices at Básico 1 activity			Rhythm at Básico 1			Consistency at Básico 1, song 'Nosso Xote'			
	Slow Paced	Medium Paced	Fast Paced	Too Slow	Correct	Too Fast	Min	Average	Std Dev	Max
Student 1	16	5	6	1	24	2	95.25	98.27	0.99	99.06
Student 2*	5	2	0	5	2	0	97.8	97.97	0.17	98.15
Student 3**	4	3	1	0	7	1	91.44	96.44	3.54	99.07
Student 4	8	6	3	2	14	1	98.32	98.54	0.16	98.8
Student 5	39	14	45	4	96	8	86.41	96.96	3.37	99.47
Student 6	11	2	8	1	20	0	97.95	98.55	0.44	99.06
Student 7	15	13	7	2	24	9	84.26	93.95	4.46	98.15
Student 8	43	11	10	21	27	16	76.5	93.76	4.69	99.93
Student 9	14	5	1	2	15	4	75.95	92.83	9.75	98.89
Student 10	12	7	3	4	17	1	93.86	97.78	1.76	98.86

Columns 2-4: Number of times practice in each level **5-7:** Detail of wrong attempts when compare to the song **8-11:** Statistics on the consistency score
*Did the exercises without attending to the classes ** Withdrew from the study

- Dos Santos, A., Yacef, K., & Martinez-Maldonado, R. (2017). Let's Dance: How to Build a User Model for Dance Students Using Wearable Technology. In *Proceedings of the 25th Conference on User Modeling, Adaptation and Personalization* (pp. 183–191). New York, New York, USA: ACM Press.

Literature review

K-pop recognition from Kinect data

Fig. 1. Thirteen core angles distinguishing each dance motion.

Feature Vector	KNN	SVM	ELM
	Training: set 1 , Test: set 2		
	Training: set 2 , Test: set 1		
6 significant angles	77.0%	79.5%	37.0%
	75.0%	82.0%	37.0%
6 significant angles (PCA)	76.0%	79.5%	73.0%
	73.5%	81.0%	71.5%
6 statistical angles	78.5%	82.5%	71.0%
	79.5%	82.0%	68.0%
6 statistical angles (PCA)	78.0%	82.5%	81.5%
	78.0%	81.0%	83.5%
13 significant angles	86.5%	89.5%	41.5%
	84.5%	93.0%	44.0%
13 significant angles (PCA)	85.5%	91.0%	84.5%
	84.0%	92.5%	84.5%
13 statistical angles	92.0%	93.5%	75.0%
	89.0%	92.0%	74.5%
Proposed method			
13 statistical angles (PCA)	92.5%	94.0%	**94.5%**
	88.0%	92.0%	**94.0%**

Kim, D.-H., & Kwak, K.-C. (2017). A motion analysis and classification based on PCA and ELM classifier. In *2017 International Conference on Advanced Informatics, Concepts, Theory, and Applications (ICAICTA)* (pp. 1–4). IEEE.

Literature review

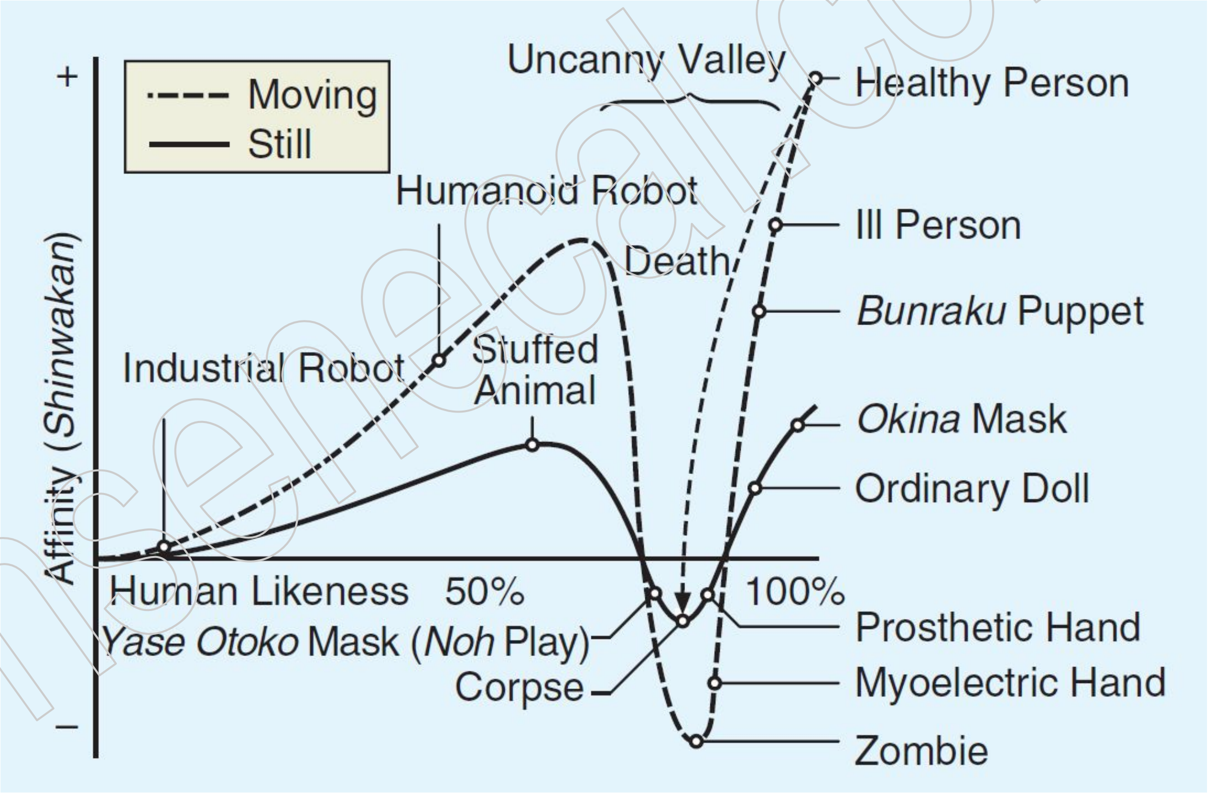
Male-type dance robot

- Ability to move in space
- Have a force feedback module for the hands
- Learning shows good results

Paez Granados, D. F., & Kosuge, K. (2015). Design of a Male-type Dance Partner Robot for leading a physical Human-Robot Interaction. *2015 IEEE International Conference on Mechatronics and Automation, ICMA 2015*, 1234–1240.

Literature review

The virtual partner should avoid resembling to a zombie !



Mori, M., MacDorman, K., & Kageki, N. (2012). The Uncanny Valley [From the Field]. *IEEE Robotics & Automation Magazine*, *19*(2), 98–100.

Machine learning:

Multi class classifier with the level of the couple as output and tested for accuracy.

Weighted K-Nearest Neighbour

- Metric: City block
- Distance weight: squared inverse
- Neighbours: 10

Random Forest

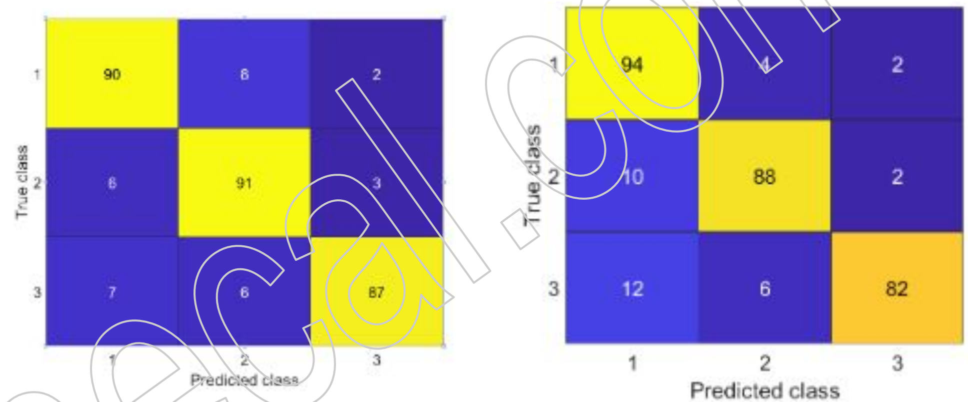
- Bagged tree
- 30 learning cycle

Cubic Support Vector Machine

- One vs One
- Box constraint level1

Chapter 2

Recall (R) = TP / (TP + FN)
Precision (P) = TP / (TP + FP)
Accuracy (A) = (TP+TN)/(TP+TN+FP+FN)



(a) Basic steps sequence (percentage)

(b) Improvisation sequence (percentage)