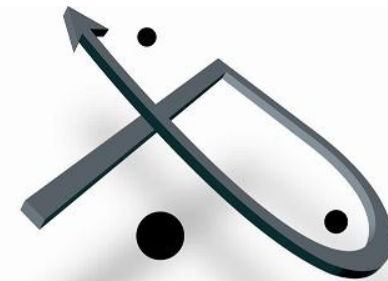


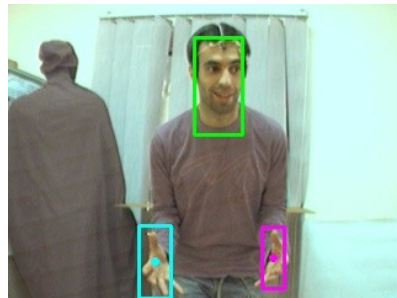


**BACS-RM 2009
Project Review Meeting
@ Zurich, Switzerland**

Laban Movement Analysis: Towards Behavior Patterns



Probayes
Mastering Uncertainty
Grenobl



Luis Santos



Jorge Dias



Juan-Manuel Ahuactzin

Summary

- Brief introduction to Laban Movement Analysis(LMA)
- Introduction to Database (Contextualize with Bayesian Approach)
- Review of LMA principles within Bayesian framework (Jorg Rett Ph.D Thesis)
 - Components and Bayesian models.
- Results for implemented Laban Components
- Multi-Ocular approach for movement analysis
- Anticipation and certainty, a consequence of bayesian approach.

Conclusions

· Defining Laban Movement Analysis

· LMA

· Introduction

· Database

· LMA:

· Description
and Models

· Learning

· Classification

· Results

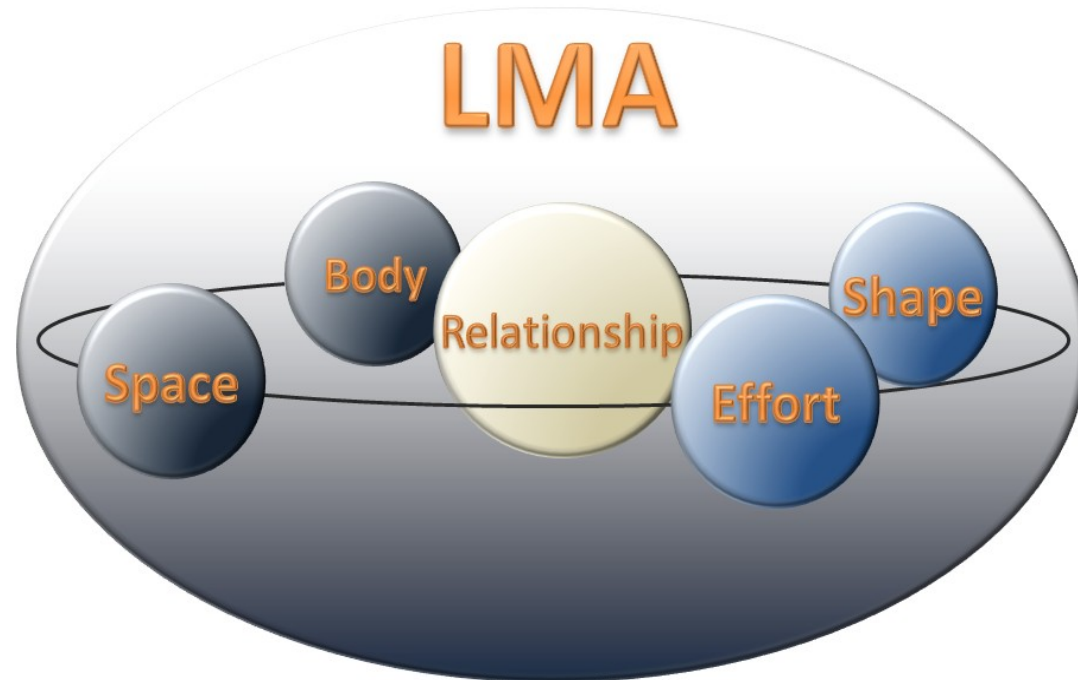
· Multi-Ocular

· Anticipation

· Conclusions

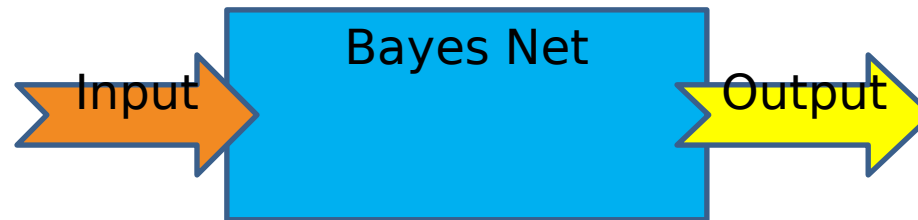
· Future

- Language to describe dancing movements (Rudolf Laban 1879-1958)
- Helps to identify useful low-level features.
- Defines a framework of mid-level descriptors for properties of a movement.
- Provides intuitive way of building a Bayesian framework for classification of expressive movements.



- Database of Expressive Movements (1)

- **Bayesian Framework**



- Input: Set of observable Low Level Features (LLF)

- Bayes Net: Probabilistic approach built from Bayesian framework

- Output: Result in form of probabilistic distribution

- Database of Expressive Movements (2)

- **Existing Databases**

- Set I : Designed to study Space Component, 8 different movements.
- Set II : Designed to study Effort Component, 4 different movements.

- **Feature extraction**

- Features are physical characteristics taken from the mapped 3-D discretized trajectories. (displacement vectors, velocity, etc)

- **New database**

- Set I: 6 Singular Movements, performed by 10 different people, 10 trials/movements (ongoing work)
- Set II: 6 Duals Movements (2 person interaction, in predefined standard actions), 6 different pairs of persons, 10 trials/pair. (follow-up set I)

- Aprox 1200 Trials Overall

Database of Expressive Movements (3)

in progress

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BACS
BAYESIAN APPROACH TO COGNITIVE SYSTEMS

BACS Project: Data Collection Database

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Project Summary

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Logic is both the mathematical foundation of rational reasoning and the fundamental principle of present day computing. However, logic, by essence, is restricted to problems where information is both complete and certain. Within the BACS project the Bayesian mathematical framework is proposed as an alternative computing framework capable to deal with incompleteness and uncertainty. The main scientific objectives of this project are:

1. To demonstrate that Bayesian probability theory is a feasible alternative mathematical framework.
2. To propose a new modeling methodology to both, better understand the cognition of living beings, and to build more efficient artificial cognitive systems.
3. To validate the whole approach by demonstrating effective Bayesian cognitive models for living beings and artificial systems by producing results. This can clearly and objectively be assessed with new designed experimental paradigms.

Human-machine Interaction

Monitoring signals
Sensory information
Bayesian controller
Motor commands
Enhanced feedback

Autonomous system

Human Robot

World

Image-Formation
Measurement space
Perception
Inverse imaging function
State space world
Action
Observer
Object models
View-Point
Ego-Velocity
World-Velocity
Scene parameters
State space observer

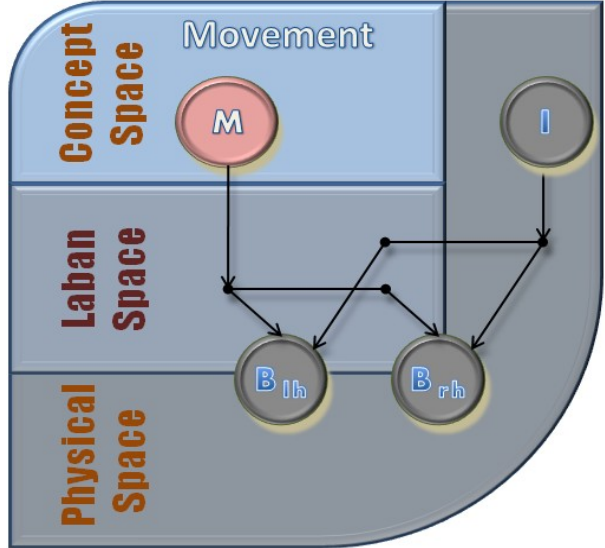
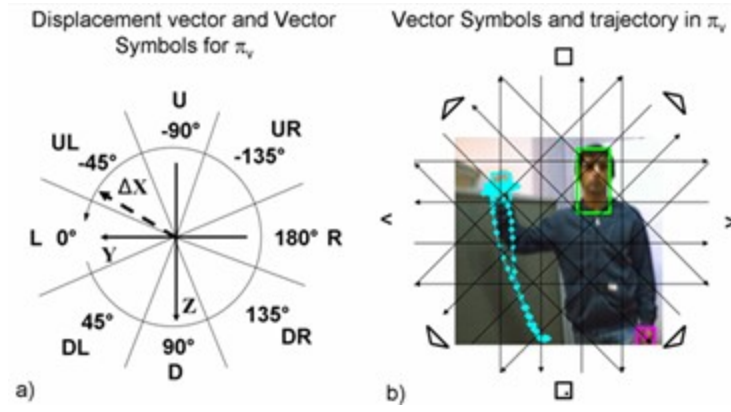
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UBUNTU APACHE MySQL POWERED PHP POWERED FIREFOX

Kinematic Components

- LMA
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- **Space**
 - Deals with spacial displacements in form of vectors (atoms).
 - Extracted directly from the spacial characteristics of the trajectories resulting from movement execution.



· **Space Bayesian Model**

Probability distribution of a movement M given frame I and Atoms B for left and right hands

$$P(M | B_{lh} B_{rh}) = P(M) P(I) P(B_{lh} | M I) P(B_{rh} | M I)$$

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- **Body**

- Closely related to space component;
- Concerns relative movement of body parts related to body center;

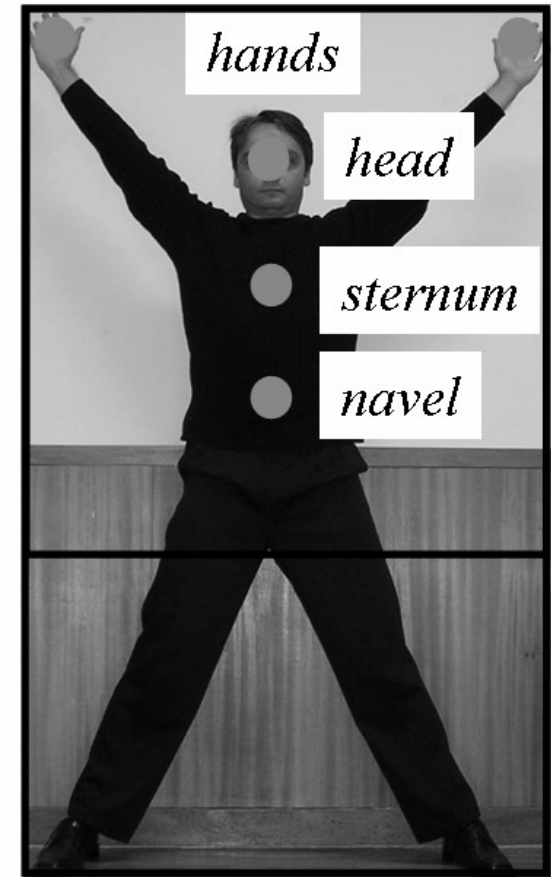
· **Body Bayesian Model** Which body parts are moving.

In development

Notes:

- we consider the center of mass of the body to be in the sternum.
- Features: euclidean distance, body part (and maybe velocity and acceleration).

LMA Body component



- Non-kinematic Components

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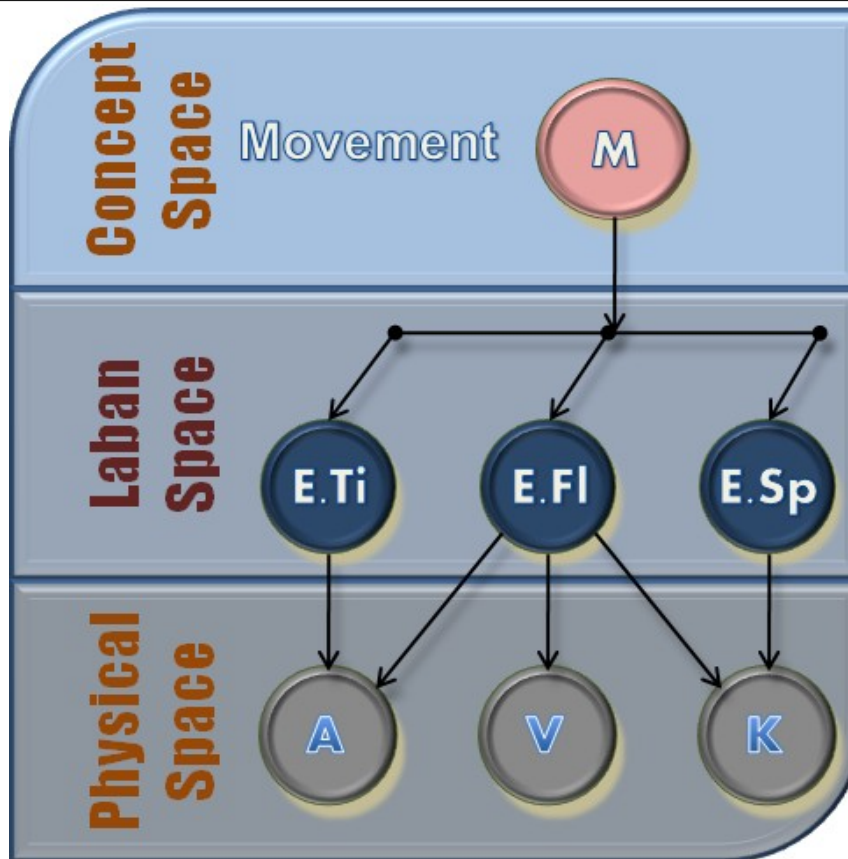
- **Effort**

- Dynamic qualities of the movement.
- Inner attitude towards using energy
- Probably the decisive component when dealing with 'expressiveness'
- Has four qualities

LMA Effort Qualities	Physical entities
<i>Time.sudden</i>	High acceleration, High velocity
<i>Time.sustained</i>	Low acceleration, Low velocity
<i>Space.direct</i>	Small curvature, Small angular velocity
<i>Space.indirect</i>	High curvature, High angular velocity
<i>Flow.free</i>	High curvature, High angular velocity
<i>Flow.bound</i>	Low acceleration, Low velocity
<i>Weight.strong</i>	Muscle tension, Medium acceleration
<i>Weight.light</i>	Muscle relaxed

- Non-kinematic Components

- Effort Model



- Effort Time

$$P(M \ E.ti \ A) \\ = P(M) P(E.ti|M) P(A|E.ti)$$

- Effort Space

$$P(M \ E.sp \ K) \\ = P(M) P(E.sp|M) P(K | E.sp)$$

- Effort Flow

$$P(M \ E.fl \ V \ A \ K) \\ = P(M) P(E.fl|M) P(V|E.fl) P(A|E.fl) \\ P(K|E.fl)$$

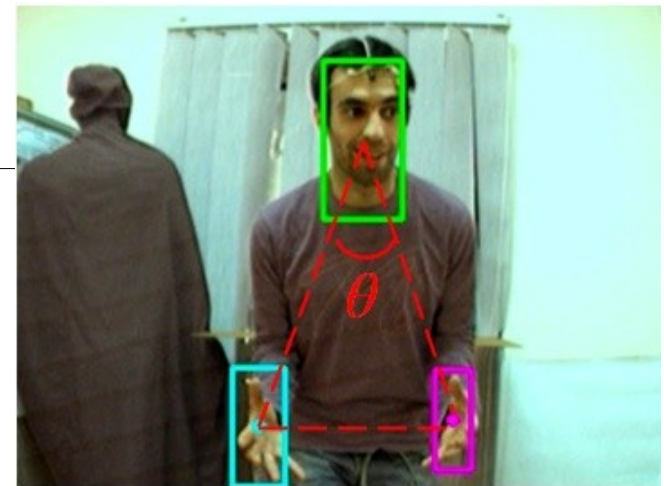
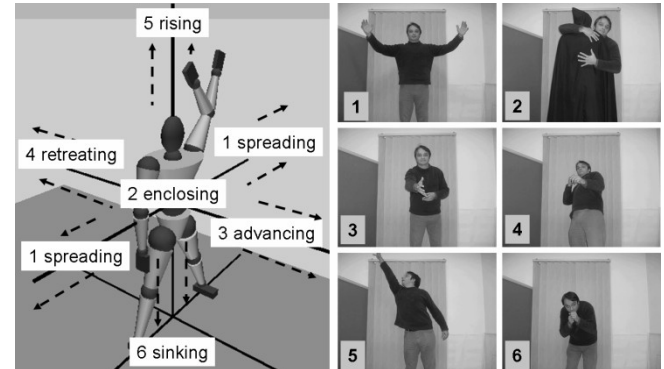
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Non-kinematic Components

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Shape

- Emerges from Space and Body components;
- Focus on: body itself, a goal towards space,
- Uses descriptors like *shrinking* and *growing*, *bulging* and *hollowing*;



Shape Bayesian Model

Ongoing work

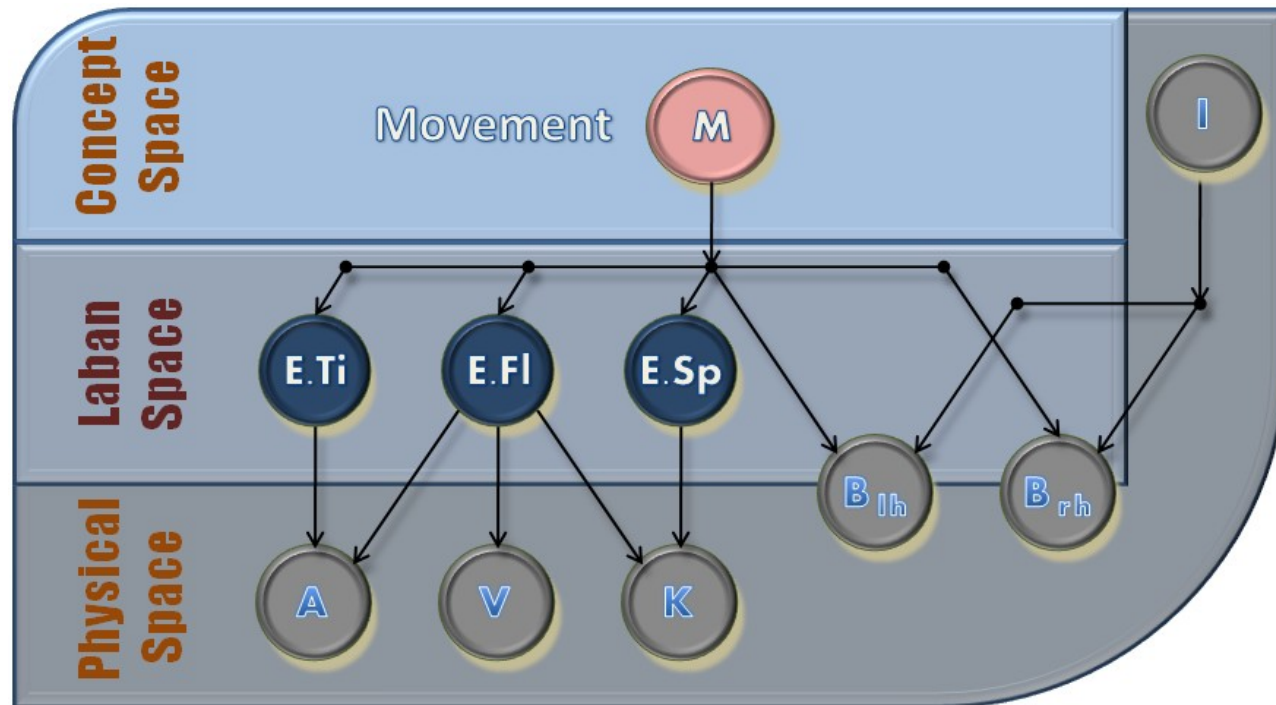
Notes:

- Consider the triangle formed from the head and hand positions
- Features: Angle θ , size (perimeter) of the triangle (the angle and the perimeter will give good descriptors on whether the expressive movement is

growing/shrinking)

- Global Bayesian Framework

- Global Model



- Bayesian Global Model**

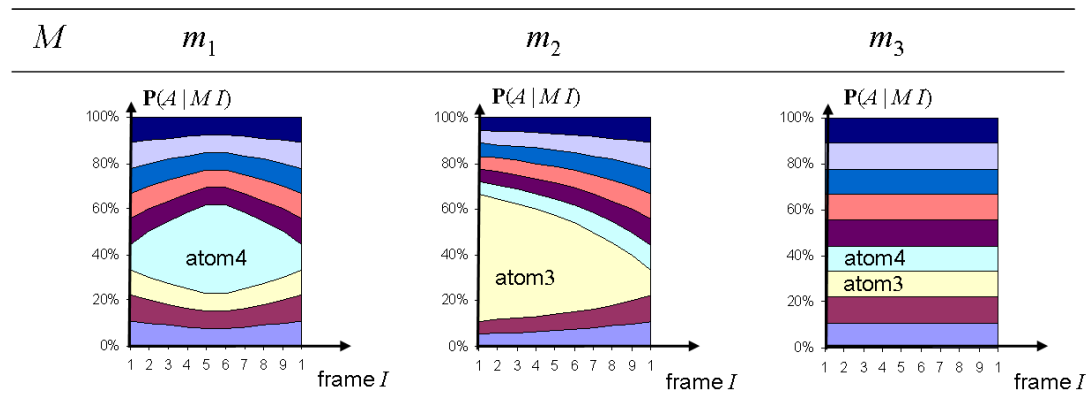
$$P(M \ E.ti \ E.sp \ I \ Brh \ Blh \ V \ A \ K) = P(M) P(M|Brh) P(M|Blh) P(E.ti|M) P(E.sp|M) P(E.fl|M)$$

$$P(A|E.ti) P(K|E.sp) P(V|E.fl) P(A|E.fl) P(K|E.fl)$$

- Learning (1)

- Scheme based on histogram approach

·Space



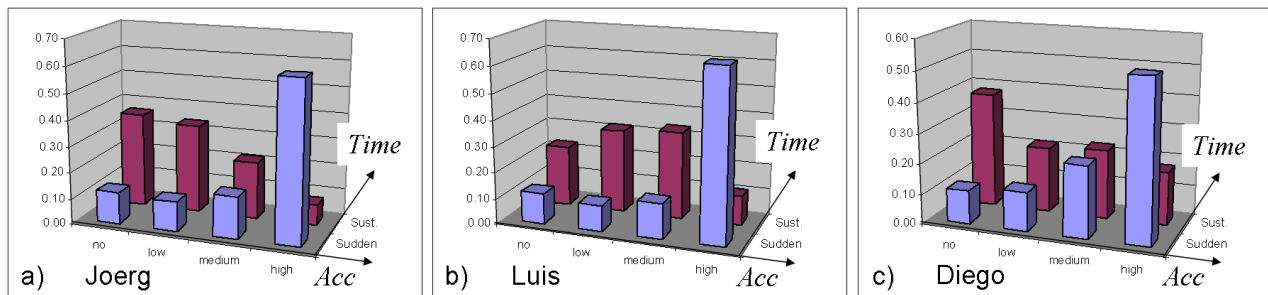
$$P(B|MI)$$

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- Learning (2)

- Scheme based on histogram approach

- Effort



$$P(LLF|Effort)$$

$$(e.g. P(A|E.ti))$$

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- Classification

- **Questions for Classification**

	Question
Space	$P(M i b) = P(M) P(b M i)$
Effort	$P(M E.ti E.sp) = P(M) P(E.ti M)P(E.sp M)$
Joint	$P(M i b E.ti E.sp) = P(M) P(i_{obs} i) P(b M i) P(E.ti M) P(E.sp M)$

- **Continuous Classification:**
Based on a scheme of likelihood computation.

E.g. For Space Component: For a sequence of n observations of a .

$$P(M_{n+1}|i_{1:n+1} b_{i:n+1}) = P(M_n) P(b_{n+1}|M_{i:n+1})$$

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- Multi-Ocular
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- Results

- LMA
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- Results**
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- Effort Qualities Classification Results

	Effort Qualities					
	Space		Time		Flow	
	Direct	Indirect	Sudden	Sustained	Free	Bounded
C.R.	79.3%	90.2%	84.8%	97.1%	61.2%	58.7%

- Overall Classification Results

	Laban Component		
	Space	Effort	Effort+Space
C.R.	61.3%	86.4%	79.4%

·C.R. : stands for *Classification Rate*, or the number of positive identifications.

Space Component Result Analysis (1)

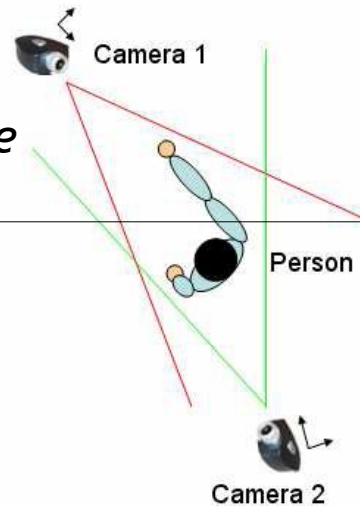
Overall Classification Results

Laban Component			
	Space	Effort	Effort+Space
C.R.	61.3%	86.4%	79.4%

· *Space* results are not as good as they could be.

· *Main reasons?*

- *Occlusion*
- *Rotation Invariance*



· **Additional advantages:** Unconstrained movement and extra

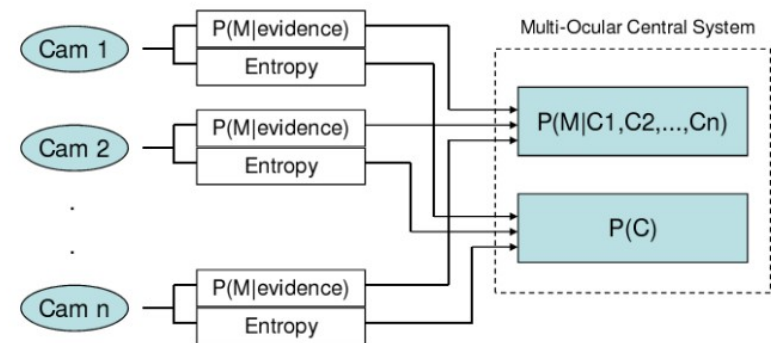
Space Component Result Analysis (2)

·Solution proposed: Multi-Ocular Model

·Each monocular system provides a probability distribution (as $P(M|C)$) of movement M for each camera C and entropy value;

· $P(C)$ is the confidence distribution for each camera, calculated through entropy values;

$$P(M) \propto P(C)P(M|C)$$

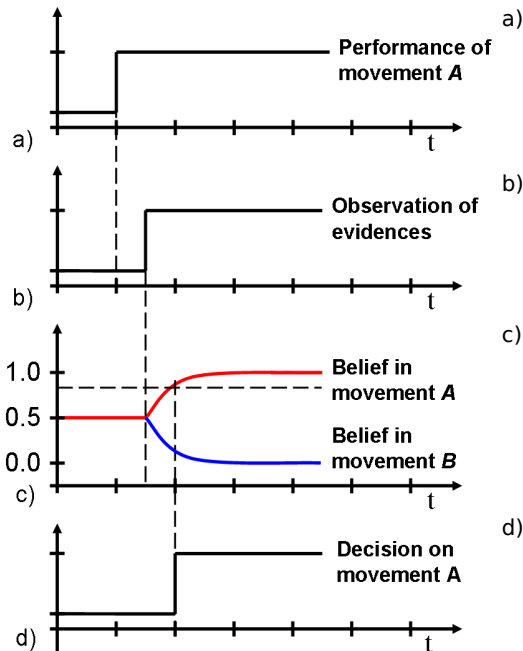


·Results: Multi-Ocular Model

C.R.	Space Component	
	Monocular	Multi-Ocular
	61.3%	81.0%

Anticipation and Certainty

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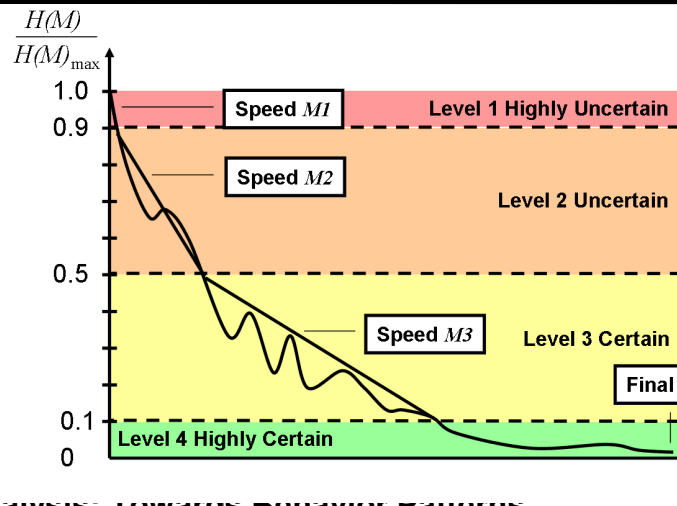


a) Subject starts to perform movement

b) After a short period, evidences start to be computed;

c) A few instants later, a certainty measure (entropy) is computed derived from probability distributions.

d) measure (entropy) triggers what will be the final result.



Highly Uncertain: $H(M)_{max} \geq H(M) > 0.9H(M)_{max}$

Uncertain: $0.9H(M)_{max} \geq H(M) > 0.5H(M)_{max}$

Certain: $0.5H(M)_{max} \geq H(M) > 0.1H(M)_{max}$

- Conclusions

- There are 2 main conclusions from this year's development

1. Multi-Ocular improved spacial results (from 61.3% classification rate to 81%)

2. Effort improved results (from 61.3% classification rate to 86.4%.)

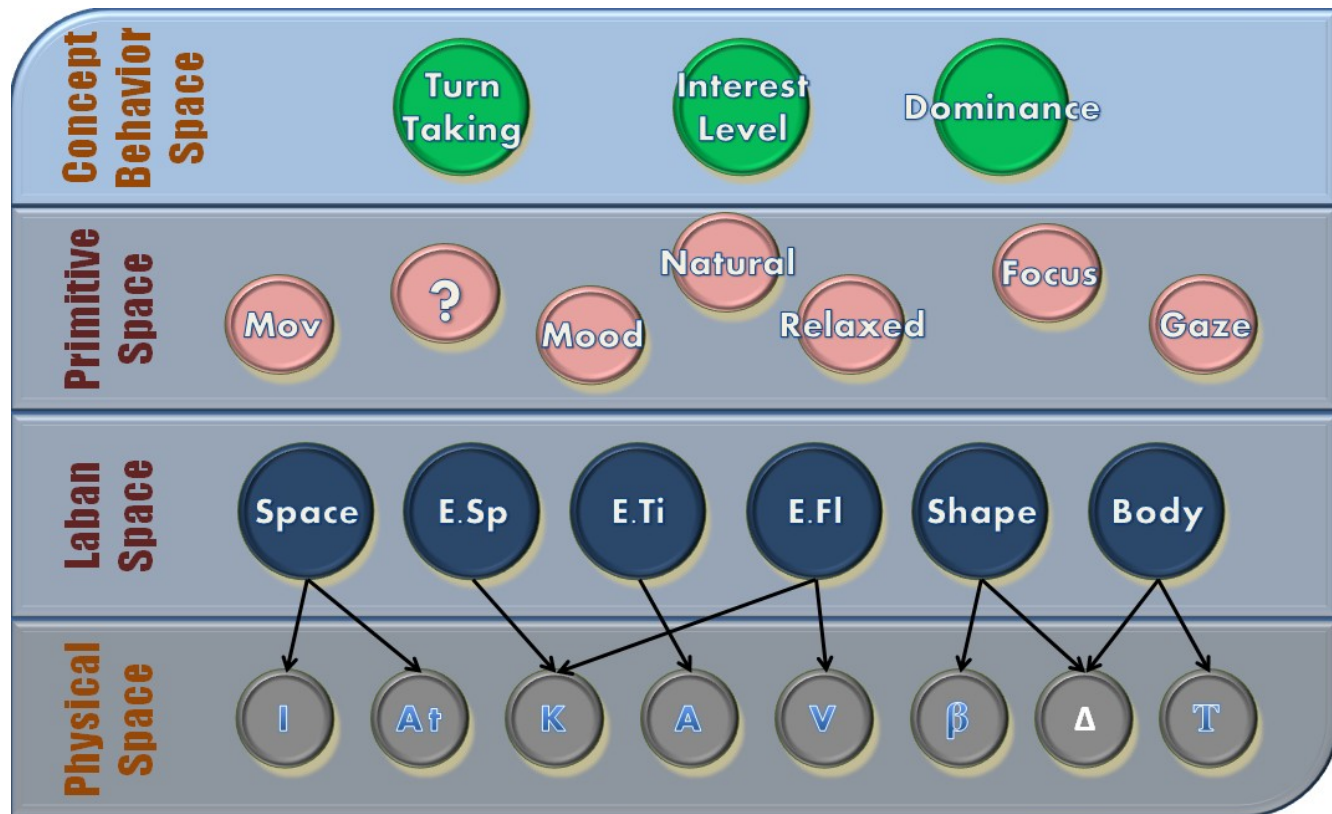
- When joining Effort and Space components
- Effort.Weight is still being investigated for visual features
- Results for effort.flow are not as good as the other 2 components due to uncertainty inherent to its features and state.

Other facts:

- The process of implementing *effort* was accomplished.
- The Bayesian approach was used for multi-ocular model designing.
- Having online-classification opens the possibility for anticipatory behaviour.
- Entropy can be used as a measure of certainty

Future Work: Towards Behavior Patterns (1)

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· Future Work: Towards Behaviour Patterns (2)

We intent:

- Implement remaining LMA Components (Body and Shape).
- To use LMA components to describe basic primitive behaviour.
 - (e.g. Aggressive, natural, gaze, etc.)
- To use those basic primitives to describe and classify more complex behaviour within the context of Small Group Conversations.
 - Turn Taking
 - Interest Level
 - Dominance
- Build a database of multiple people interacting within the already reference context.
- Build Bayesian models for behaviour classification.

- LMA
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- **Future**

Thank you for your
attention!

· Publications & Deliverables

This research produced, along with the results shown, the following documents:

- D5.17 Laban Movement Analysis using a Bayesian model and perspective projections.
- D5.18 Bayesian Model for Computational Laban Movement Analysis.
- D5.20 Computational Laban Movement Analysis using Multi-Camera Systems.
- Joerg Rett, “Robot-Human interface using Laban Movement Analysis inside a Bayesian framework.”, PhD thesis.
- Extended abstract published in conference proceedings at “14ª Conferência Portuguesa de Reconhecimento de padrões (RecPad) 2008”
- Article “Human Robot Interaction: Studies on Laban Human Movement Analysis and Dynamic Background Segmentation”, submitted to IROS09 (In review).