Human Robot Interaction
Studies on Laban Human Movement Analysis and Dynamic Background Segmentation

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Abstract—
Human movement analysis through vision sensing systems is an important subject regarding Human-Robot interaction. This is a growing area of research, with wide range of aplications fields. The ability to recognize human actions using passive sensing modalities, is a decisive factor for machine interaction. In mobile platforms, image processing is regarded as a problem, due to constant changes. We propose an approach, based on *Horopter* technique, to extract Regions Of Interest (ROI) delimiting human contours. This fact will allow tracking algorithms to provide faster and accurate responses to human feature extraction. The key features are head and both hand positions, that will be tracked within image context. Posterior to feature acquisition, they will be contextualized within a technique, *Laban Movement Analysis* (LMA) and will be used to provide sets of classifiers. We will use these classifiers to label/classify human emotion within the context of expressive movements. Compared to full image tracking, results improved with the implemented approach, the *horopter* and consequently so did classification results.

I. Introduction

Human movement analysis is a growing area of research, and being target of a large number of surveys. Gavrila [5] points out that the ability to recognize human movements and their activities using passive sensing modalities, namely vision, is a key factor for machine interaction in an inteligently and effortlessly fashion within a human-inhabited environment. Human-machine interaction can beneficiate from this simple sensor, allowing 'communication' to become easier and uncumbersome. We will use a technique, named *Laban Movement Analysis* (LMA) in order analyze human gestures. This LMA based classifiers will use low-level-features that provide descriptors of human emotion within the context of expressive movements. These descriptors will be extracted from the spatial trajectories of body parts along the time. The key features are head and both hands positions, that will be tracked within image context. However, in mobile human-interacting platforms, image processing can pose as problem, due to dynamic characteristics of the elements in the image. We propose to use the *geometric horopter* defined by the vision system, to extract Regions Of Interest (ROI) delimiting human contours. The consequence of reducing the search area to these ROI's in the image, will allow the tracking algorithm to provide faster and accurate response to body part position extraction.

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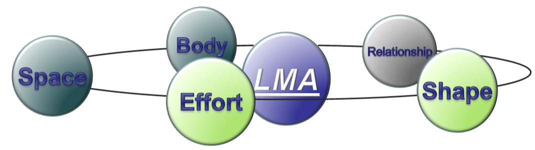

Fig. 1. The 5 LMA components.

II. Basic Concepts

A. Laban Notation and Bayesian Approach

Laban Movement Analysis (LMA) is a method to observe, describe, notate and interpret human movement, developed by Rudolf Laban (1879 to 1958). The general framework is widely applied in physical and menthal therapy [1] as well as studies of dance, however, it has found little application in the engineering domain. Recently, researchers (e.g. [4]) from neuroscience started to investigate LMA as a tool to describe certain effects on the movements on animals and humans. A recent study on LMA by Rett J. [9], explored how LMA can be used to classify human expressive movements within human-machine interaction. A robot interface was developed using LMA, giving it the capability to interpret a set of basic human movements. Rett's work also states that LMA has the potential to analyze emotional content of human actions.

The theory of LMA consists of several major components, though the available literature does not set a standard regarding their total numbers. The work of Norman Badler's group [3], [11] mentions five major components shown in Fig 1

Non kinematic components: *Body* specifies which body parts are moving, their relation to the body center; *Space* deals directly with the trajectory executed by the body parts while performing a movement. Within the **Kinematic** ones there are: *Effort* which deals with the dynamic qualities of the movement, and the inner attitude towards the use of energy; *Shape* (emerging from *Body* and *Space*) is focused on the body itself. Then we have *Relantionship* that appears as the less explored component, and describes the interaction with oneself, others and the environment. Some literature only considers the first four mentioned components [4]. The *Space* component has already been studied by Rett et. al. [7], though in his recent study [9], space was left for improvement on the *Effort* compoment, in order to study the emotional content of expressive movements. This *Effort*

TABLE I

Effort QUALITIES AND THEIR SUBJECTS

Effort	Cognitive process	Subject	Extremes
Space	Attention	The spatial orientation	focused or non-focused
Weight	Intention	The impact	strong or light
Time	Decision	The urgency	urgent or non-urgent
Flow	Progression	How to keep going	free or careful

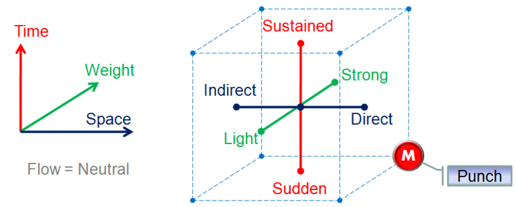

Fig. 2. The bipolar *Effort* qualities of the *Action Drive*, i.e. *Flow = neutral* (omitted) represented as a cube. The position of the movement M (*punch*) indicates its qualities, i.e. *direct*, *sudden* and *strong*.

component will be the main focus of movement analysis in this work, hence it will be described.

Effort

What makes the framework of LMA so special is its ability to describe an additional 'expression' that accompanies the spatial trajectory (*Space* compoment). This might be the key to retrieve some evidences about the emotional state or the intention of the performer. Thus, the *Effort* component can be seen as the key descriptor to solve the task of analyzing 'expressive movements'.

Effort describes the dynamic qualities of the movement and the inner attitude towards using energy. It consists of four *Effort* qualities: *Space*, *Weight*, *Time*, and *Flow*. Table I shows the *Effort* qualities, the underlying cognitive process, the subject and the two extremes each quality has [1]. Each quality is bipolar and its values lie between two extremes. The values for the *Effort* qualities are shown in (1)

$$\begin{aligned} Space &\in \{direct, neutral, indirect\} \\ Time &\in \{sudden, neutral, sustained\} \\ Weight &\in \{strong, neutral, light\} \\ Flow &\in \{bound, neutral, free\} \end{aligned} \tag{1}$$

Movements are described and distinguished by those qualities that are close to an extreme, e.g. a *Punch* has *Strong Weight*, *Sudden Time* and *Direct Space*.

Combinations of all four qualities rarely occur as they produce extreme movements (e.g. tearing something apart) [1]. Single-quality movements are also rare [1] [11]. Combinations of three qualities, with the fourth considered to be neutral, appear to be the most natural way to perform an action. Each of these combinations, can be modulated to define a 3-D space, a cube where each vertex represents a sub-component (Fig. 2).

These combinations of three *Effort* qualities can be divided into four cathegories: *Action Drive, Weightless, Timeless* and *Spaceless*. Each of these cathegories considers as being neutral, the *Flow, Weight, Time* and *Space* respectively.

B. Bayesian Networks

Prior to the discussion of the concepts and the framework itself, the introduction of some mathematical principles is necessary. Our approach is based in a Bayesian framework, that includes specialized models such as Hidden Markov Models (HMMs), Kalman Filters and Particle Filters.

The first concept that will be presented is the usual notion of *logical proposition* ([2]). A logical *proposition* can be either true or false. *Propositions* are denoted by lowercase names. *Propositions* may be composed to obtain new propositions using the usual logical operators: $a \wedge b$ denoting the conjunction of *propositions* a and b, $a \vee b$ their disjunction and $\bar{a}$ the negation of *proposition* a.

Variables are denoted by names starting with one uppercase letter. A discrete variable X is a set of logical *propositions* x_i which means that the variable X takes its ith value. These logical *propositions* are mutually exclusive and exhaustive. $\langle X \rangle$ denotes the cardinal of the set X. A variable $\mathbf{X}$ that is a vector or a set of variables is indicated by bold letters.

To be able to deal with uncertainty, we attach probabilities to *propositions*. To each *proposition* a a unique real value $P(a)$ in the interval $[0, 1]$ is assigned.

One interesting case is the probability of conjunctions $P(a \wedge b)$, disjunctions $P(a \vee b)$ and negations $P(\bar{a})$of *propositions*. Another is the probability of *proposition* a conditioned by some other *proposition* b i.e. $P(a|b)$.

Probabilistic reasoning needs only two basic rules. The first is the *conjunction rule of propositions*, which gives the probability of a conjunction of *propositions*. While omitting the conjunction symbol we can state:

$$\begin{aligned} P(a\ b) &= P(a) \times P(b \mid a) \\ &= P(b) \times P(a \mid b) \end{aligned} \tag{2}$$

The second one is the *normalization rule of propositions*, which states that the sum of the probabilities of a and $\bar{a}$ is one.

$$P(a) + P(\bar{a}) = 1 \tag{3}$$

The two rules (2, 3) are sufficient for any computation in discrete probabilities. All the other necessary inference rules concerning *variables* can be derived from these.

C. Interaction Zone and Dynamic Backgrounds

Within the context of human-robot interaction, there is a pre-requisite, the need for the robot to recognize the person with whom it will interact. Usually it is done using a video sensing. Since the system is implemented in a mobile platform, to separate the person from the background demands

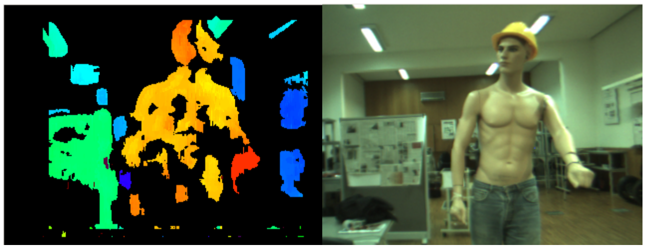

Fig. 3. a) Depth map (*'hot'* colors represent nearest areas, *'cold'* colors represent further ones; b) Dominant eye raw image

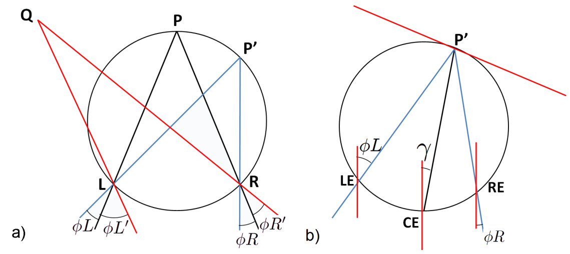

Fig. 4. a) Calculating the Disparity; b) Disparity Properties on Vieth-Muller Circle

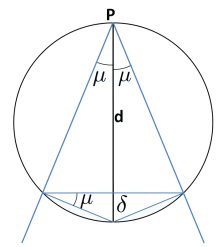

Fig. 5. Simples justification scheme for value γ

more complex processing, due to dynamic characteristics of the background. This means that an approach based in static background, as in [10] and [8], is not possible. The challenge was thus to have a robust real time solution for dynamic background segmentation on mobile robotics. Our approach is based on the *Geometric Horopter*. This technique used stereo vision to produce a *depth map*. It is presented in Fig.3 a) the *depth* map resulting from the application of this algorithm, whilst the right side shows the image from one of the stereo cameras.

The application of the *horopter* will introduce a definition, the *interaction zone*. As it will be explained in the next section, a circle will be define, and the inside area of that circle is the interaction zone. This means that if a person is detected inside it, it is passible of being detected, and thus to interact with the robot.

D. Geometrical Horopter

1) Horopter Segmentation :

a) Properties of ViethMuller Circle: The concept of *interaction zone* has been defined as dependent of a circle. That circle is called the Vieth-Muller Circle, nas the following properties can be defined (See Fig.4):

- In a pure version eye movement, the fixation point stays on the same ViethMuller Circle. Fig.4 a) illustrates this fact showing how P moves to P' along the Vieth-Muller Circle.
- It the fixation point remains static, the disparity for various points is studied. Disparity is defined as ϕL ϕR.

b) Theorem 1: If a point Q lies on ViethMuller Circle, its disparity is zero.

As Q moves outside (e.g. point P moves to position Q in Fig.4 a)), ϕL decreases whilst ϕR will naturally increase. However ff point Q moves inside the circle, the opposite relation between ϕL and ϕR occurs.

c) Theorem 2: Disparity is nonzero outside the circunference line of the Vieth-Muller Circle (with opposite signals, depending on whether side of the circle it lies in, outside or inside).

For human vision system, when the disparity has high enough values, the object is seen in double (one from left eye and the other from right eye). This phenomenon is called *Diplopia*. The maximum disparity prior to the diplopia even is defined as *Panum's Fusional Limit*.

d) Calculating Disparity: The ϕL and ϕR are made by line of sight with the straight ahead direction. The $GazeAngle$ γ (see Fig.4 a) and $VergenceAngle$ μ (see fig. 5) are defined as

$$\begin{aligned} \gamma &= \frac{1}{2}(\phi L + \phi R) \\ \mu &= \frac{1}{2}(\phi L - \phi R) \end{aligned} \tag{4}$$

CE represents the cyclopean eye and $(d + \delta)$ is the distance from CE to the target object (see fig. 5).

The Horizontal Disparity is

$$h = \frac{I \cos\gamma}{d}\left(\frac{\delta}{\delta + d} + \frac{d \tan\gamma}{\delta + d} x + x^2\right)$$

and Vertical Disparity

$$v = \frac{I \cos\gamma}{d}\left(\frac{d \tan\gamma}{\delta + d} y + xy\right)$$

where (x, y) are cyclopean image coordinates and I is the interocular distance.

e) Theorem 3: $d = I \cos\gamma / \sin 2\mu$

A simple justification can be presented for the value of $\gamma = 0$, as it can bee seen in Fig.5.

$$I/2 = d \times \sin u \times \cos u \Rightarrow d = I \cos r / \sin 2u$$

Having disparity calculated, the resulting depth image (Fig.3 a)) is correlated with the CE image. Pixels that present negative values for disparity, will be assigned zero value (black color pixels). The result is a segmented image where

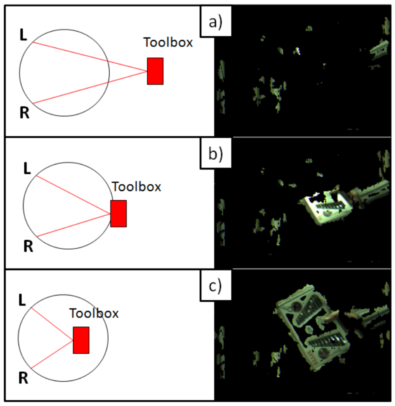

Fig. 6. a) The toolbox is yet outside the Vieth-Muller Circle; b) Toolbox starting to enter the horopter zone; c) The object is fully inside the Vieth-Muller circle, and thus, visible.

TABLE II
Basic Effort Weightless

Action	Example	E.Sp	E.Fl	E.Ti
Punch	Forward punch	Dir	Bound	Sud
Writting	Write name with a spray can	Ind	Free	Sus
Lift	Lift heavy object	Dir	Bound	Sus
Flick	Clean with a brush	Ind	Bound	Sud
Free scene	Free movements	misc	misc	misc

the pixels calculated to be inside the *Vieth-Muller* circle define the 'visible' objects within the circle (the interaction zone). The segmented image (right column of figure 6) results in a region of interest, that can be approximated for an elipse, and will define the input for the *face/hand* detector and feature processing. Consequently the robot will interact only with subjects inside *Vieth-Muller* circle, or in other words, inside its current horopter.

III. Human Robot Interaction

A. Database of Expressive Movements

According to LMA Effort definitions of *Action drive, Timeless, Weightless* and *Spaceless*, there are 32 different possible combinations. This work is focused on *Effort* component (work on *Space* component has been done in [7]), thus *Space* component has no particular relevance in this set of results. The database was build around movements that present certain *Effort* characteristics, in a way that will allow the *Bayesian Classifier* to accurately provide an *Effort* labelling of the movements, based on LMA. Table II shows a set of *Weightless* expressive movements and their qualities.

The data set also encompasses a free scene hand labeled, were several of the *Effort* characteristics were performed along the time.

B. Tracking

Data acquisition is processed using two different types of sensor:

1) a 6-DoF magnetic tracker that provides 3-D coordinates with high accuracy and speed (50Hz),

TABLE III
Initial hypotheses of correspondences between LMA *Effort* qualities and physical entities

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

2) a regular firewire camera.

The data collected using the magnetic tracker is directly read from the sensors itselves, which are attached to specific body parts (both hands and the head). Concerning the camera, a simple algorithm was implemented.

Algorithm 1 Tracking Algorithm based on Horopter and CAMshift

1) Image acquisition
2) Geometric horopter segmentation
3) Haarlike feature detection to detect face.
4) Tracking based in CAMshift and Kalman Filter.

The Haarlike features and CAMshift algorithm used, belong to the already mentioned OpenCV Library. This vision algorithms are applied on the segmented image resulting from the application of the *Geometric horopter* described in section II-D. The CAMshift algorithm uses geometric constraints for faster initialization and tracking of body parts (Head and both Hands).

The final result, from each of the sensors, is a collection of hand and head coordinates in 3-D and 2-D space for magnetic tracker and camera respectively. In order to have the same dimension, 3-D points from Magnetic tracker are mapped into 2-D space as if they were seen by the camera. This process was done considering calibrated camera and magnetic tracker. The process of calibration was done using projective geometry [6].

C. Prominent physical features

The selection of relevant features is one on the great mysteries in pattern recognition. In this work, features were chosen by interpreting the parameters of Laban Movement Analysis (LMA) through physical measurable entities that could describe them best. The resulting data is in form of coordinates, which allows the computation of physical features such as velocity, acceleration and curvature of the discretized trajectories. Having this sets of features in mind, the initial hypotheses of correspondences between LMA parameters and physical entities are expressed as shown in Table III.

A work has been made in order to analyze how these features behave in each of the qualities, and the most prominent are marked in bold in table III. As it can be

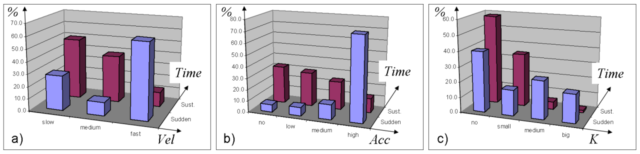

Fig. 7. Behavior of Velocity V, Acceleration A and Curvature K in *Effort Time*

seen, this work still has not found physical features that can inequivocally define *Ef.Weight* (there is no visual cue that could reflect muscle tension). However, ongoing work is still being conducted focused on visual cues that could reflect it. In Fig. 7 an example of physical features behavior in a determined *Effort* quality is presented. Velocity (Fig.7a)) and curvature (Fig.7c)) do not present a strong pattern that can distinguish both extremes of *E.Ti*, however Acceleration (Fig.7b)) presents a strong, distinguishable feature.

All features are identically processed, originating the final relations for the models presented in table III.

IV. Probabilistic Modeling

A. Effort Model

The *Effort model* describes the dynamic aspects of the movement. It relates the low-level features like speed (Vel), acceleration (Acc) and curvature (K) to *Effort* qualities like *Time* ($E.Ti$), *Space* ($E.Sp$), *Weight* ($E.We$) and *Flow* ($E.Fl$). In order to not confuse the *Space* **component** from the previous section with the *Space* **quality** of the *Effort* component, all variable symbols of Effort qualities are preceded by a leading E.

$$\begin{aligned} \mathbf{LLF}_{Ef} &\in \{Vel, Acc, K\} \\ \mathbf{Effort} &\in \{E.Ti, E.Sp, E.We, E.Fl\} \end{aligned} \tag{5}$$

The relation between the two sets of variables described in 5 has already been investigated, established and developed in Section III. The *concept space* relates the *Effort* qualities to a specific movement M. The *Effort model* is related with a specific plane and body part where the *Effort* qualities can be detected best. Variables and their space are shown in (6)

$$\begin{aligned} Acc &\in \{no, low, medium, high\}\ \langle 4\rangle \\ K &\in \{no, small, medium, big\}\ \langle 4\rangle \\ E.Sp &\in \{direct, indirect\}\ \langle 2\rangle \\ E.Ti &\in \{sudden, sustained\}\ \langle 2\rangle \\ E.Fl &\in \{free, bounded\}\ \langle 2\rangle \end{aligned} \tag{6}$$

Each movement M will produce a certain set of *Effort* qualities during the movement action. Thus we have a conditional dependency of *Effort Space* $E.Sp$, *Effort Time* $E.Ti$ and *Effort Flow* $E.Fl$ from the movement M as can be seen in Bayes-net of Fig. 8.

The *Effort* variables can not be directly measured but observed through some low-level features (i.e. $\mathbf{LLF}_{Ef}$). Thus, there is a dependency of the non-observable variables from the *Effort* set and $\mathbf{LLF}_{Ef}$. The joint distribution can be expressed as

$$\begin{aligned} & P(M\ E.Sp\ E.Ti\ E.Fl\ Acc\ K\ V) \\ = & P(M)\ P(E.Sp \mid M)\ P(E.Ti \mid M)\ P(E.Fl \mid M) \\ & P(Acc \mid E.Ti)\ P(K \mid E.Sp)\ P(K \mid E.Fl) \\ & P(V \mid E.Fl)\ P(A \mid E.fl) \end{aligned} \tag{7}$$

The variables used in this sub-model are summarized in Table IV.

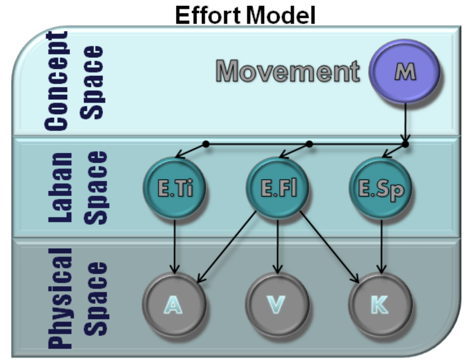

Fig. 8. Laban Effort Bayesian Model

TABLE IV
EFFORT VARIABLES

Variable	Symbol	Description
Movement	M	e.g. $Punch$
Effort Space	$E.Sp$	e.g. $E.Sp = direct$
Effort Time	$E.Ti$	e.g. $E.Ti = sudden$
Effort Flow	$E.Fl$	e.g. $E.Fl = bound$
Speed gain	Acc	e.g. $Acc = high$
Curvature	K	e.g. $K = small$
Velocity	V	e.g. $V = medium$

V. Results and discussion

This section will briefly describe the general setup, and will divide the results in two sections, the results of geometric horopter and consequent tracking and the results for the Effort analysis. Four movements and a free scene were processed, with 100 trials per movement, with 10 subjects (both gender), with no more than 10 trials per different person within each gesture.

A. Experimental Setup

A pair of *Firewire* cameras were used as the stereo vision system. Learned sequences were acquired with Magnetic Tracker Device (Polhemus Liberty). Classification was done using image video sequences which simulate real-time conditions perfectly. The analyzed movements are summed up in Sec.III-A tableII.

B. Geometric Horopter Results

The Horopter results are easily understood if visualized, hence in Fig.9 it can be seen the segmentation that occurs

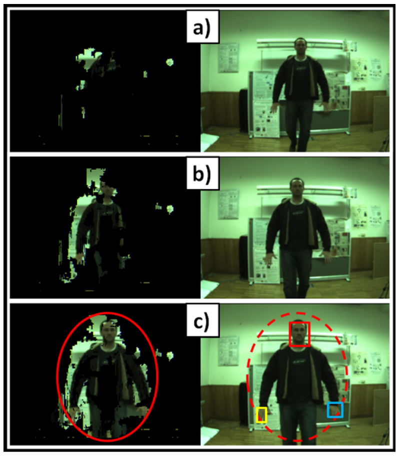

Fig. 9. a) Subject outside FoV. b) Subject entering FoV (Haarlike features try to identify a face) c) Person inside FoV, Face detected and CAMshift starts hand and head tracking

TABLE V
RESULTS FOR EFFORT QUALITIES

	Physical Qualities					
	Space		Flow		Time	
	Ind	Dir	Free	Bound	Sud	Sus
Positive results	79.3%	90.2%	61.2%	58.7%	84.8%	97.1%

with this algorithm. Once the subject enters the horopter field of view (FoV) completely, the result is a region where the person can be seen (that region tends to approximate a contour). This countor is then aproximated by an elipse (Fig.9c) left side), which defines the region where the tracking is processed (superimposed in Fig.9c) right side). Haarlike features detect a face within the delimited region (Fig.9c) right side), after which CAMshift is triggered to start acquiring information relative to hand and head positions. This algorithm is, as said, based in color histograms and kalman filtering. Cases happen where tracker is momentarily lost. In those cases, the bayesian network is not updated.

C. Emotion Analysis Results

The usefulness of Laban Movement Analysis within emotion classification is demonstrated with the results shown in table V

For *E.Time* and *E.Space* the results are considered good. However for *E.Flow* the results exhibit some confusion. This arises from the fact that low accelerations only describe the *'bound'* state of *E.Flow*, but acceleration is still counted as evidence for the *'free'* state. Similar conclusion when analyzing Curvature. *Effort* qualities, due to the number of different combinations possible, allows the possibility to distinguish movements almost based on *Effort* component. The selected features already allow a good discretization, and when combined with the other LMA components can provide a robust tool for human movement analysis. Regarding LMA combinations, we have combined

TABLE VI
RESULTS FOR EFFORT AND SPACE COMPONENTS COMBINED

	Laban Components		
	Space	Effort	Space+Effort
Classification Rate	61.3%	86.4%	79.4%

the results from *Effort* component with the *Space* component from [7] in a simple bayesian model, and defined as $P(Movement|Space.component\ Effort.component)$. Results show an increase of classification for indivual basic movements as seen in table VI. Results are continuously updated and available in `http://www.isr.uc.pt/~luis/`

VI. CONCLUSION

From the results achieve, we can conclude that horopter is a valid approach for dynamic background segmentation, provided that it receives background with enough features, which usually happens. This segmentation enhances tracking results, both in speed and accuracy and should be further explored. Laban Movement Analysis is without a doubt a powerfull movement descriptive tool, results show that it can, with some accuracy classify basic emotion primitives (contextualized within LMA), and the implementation of the remaining components is an ongoing work. The final goal of this work, is to build an autonomous interactive social robot.

REFERENCES

[1] I. Bartenieff and D. Lewis. *Body Movement: Coping with the environment.* New York: Gordon and Breach Science., 1980.

[2] Pierre Bessire. Survey: Probabilistic methodology and techniques for artefact conception and development. Technical report, INRIA Rhne-Alpes, 2003.

[3] Diane Chi, Monica Costa, Liwei Zhao, and Norman Badler. The emote model for effort and shape. In *SIGGRAPH 00, Computer Graphics Proceedings, Annual Conference Series*, ACM SIGGRAPH, pages 173–182. ACM Press, July 2000.

[4] Afra Foroud and Ian Q. Whishaw. Changes in the kinematic structure and non-kinematic features of movements during skilled reaching after stroke: A laban movement analysis in two case studies. *Journal of Neuroscience Methods*, 158:137–149, 2006.

[5] D. M. Gavrila. The visual analysis of human movement: A survey. *CVIU*, 73(1):pp. 82–98, 1999.

[6] R.I. Hartley and A. Zisserman. *Multiple View Geometry in Computer Vision*. Cambridge University Press, 2000.

[7] J.Rett, L. Santos, and J. Dias. Laban movement analysis for multi-ocular systems. In *IEEE/RSJ International Conferece on Intelligent Robots and Systems (IROS08)*, 2008.

[8] J. Meessen, C. Parisot, C. Lebarz, D. Nicholson, and J.F. Delaigle. Smart encoding for wireless video surveillance. In *In SPIE Proc. Image and Video Communications and Processing*, volume 1, 2005.

[9] Joerg Rett. *Robot-Human Interface Using Laban Movement Analysis Inside a Bayesian Framework*. PhD thesis, University of Coimbra, 2009.

[10] Theodore Totozafiny, Olivier Patrouix, Franck Luthon, and Jean-Marc Coutellier. Dynamic background segmentation for remote reference image updating within motion detection jpeg2000. In *ICIP International Conference on Image Processing*, volume 1, 2008.

[11] Liwei Zhao. *Synthesis and Acquisition of Laban Movement Analysis Qualitative Parameters for Communicative Gestures*. PhD thesis, University of Pennsylvania, 2002.