THE NEED FOR IMPULSIVITY & SMOOTHNESS
Improving HCI by Qualitatively Measuring New High-Level Human Motion Features

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Abstract: The aim of this paper is to develop algorithms to measure motion features by investigating concepts which are commonly used to describe movement characteristics in both research studies and everyday life: impulsivity and smoothness. We also aim to implement such definitions in our developing environment VisNet and finally test if they can effectively measure impulsivity and smoothness in the same way these characteristics are perceived by human users.

1 INTRODUCTION

In the last few years one of the key issues of the Human Computer Interaction framework is the design and creation of a new type of interfaces, able to adapt HCI to human-human communication capabilities. In this direction the ability of computers to detect the user emotional state is becoming particularly relevant, that is, computers must be equipped with interfaces able to establish an *Affect Sensitive* interaction with the user, in the sense defined by Zeng in (Zeng et al., 2009). Many different research activities have been performed with this aim, see for example Affective Computing in USA (Picard, 1997) and Kansei Information processing in Japan (Hashimoto, 1997). Both these areas in fact aim to design and implement machines that are able (i) to recognize user emotions, (ii) to express emotional states, and (iii) "to have" emotions. Such research objectives require skills traditionally belonging to separate disciplines, in particular computer technologies and humanistic research. The cross-modal nature of this research area is multidisciplinary also from an application point of view, as we can apply results in, e.g. rehabilitation, e-learning, e-teaching, entertainment, performing arts and so on.

In our work we focus our attention on the first of the above aspects, i.e. the ability for machines to recognize the user emotional state. Psychologists, musicologists, researchers on music perception and human movement, like Wallbott & Scherer (Wallbott and Scherer, 1986), Gallaher (Gallaher, 1992), deem it is important in recognizing emotions the evaluation of body motion qualifiers such as: speed, amplitude, energy and so on. Wallbott demonstrated in (Wallbott, 1998) that body activity, expansiveness and power are discriminating factors in communicating a large number of emotional states. In a similar approach, R. Laban elaborated his Theory of Effort (Laban and Lawrence, 1947), in which he identify some motion cues that are conveyor of high level information as emotional states. Also in music perception there are audio features responsible in communicating emotions, such features are related to tempo, volume, pitch, articulation, dynamics and so on.

In this paper we present a method for measuring two of the features mentioned above: movement impulsivity and smoothness. Impulsivity indicates wether or not movement presents sudden and abrupt changes in energy. For example, an unexpected danger like a car approaching a person crossing the street may induce a sudden and impulsive reaction in the person movement, due to the emotion of fear/terror. Smoothness identifies the continuity/fluency of movement. Happy and relaxed persons usually communicate their state by producing body movements that are very fluent and continuous. Instead, angry and tensed persons perform quick and short body movements exhibiting abrupt changes in limbs curvature/speed.

2 IMPULSIVITY DEFINITION

In this paragraph we will present the main references, from different research areas, we used to reach impul-

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sivity definition.
From physics we refer to the Impulsive Momentum TheoremIf Force and Mass are considered as constants then the following rule is respected: $I = F \triangle t = m \triangle v = \triangle p$. If the starting and the ending velocities are known then the rule above can be written as: $\triangle p = m(vf - vi)$.
The underlying concept of this theorem considers the impulse as a variation of the momentum,i.e **a perturbation of the state**, useful to reach a definition and to reach a reference measure.
In psychology Impulsivity is defined as *"actions that are poorly conceived, prematurely expressed, unduly risky, or inappropriate to the situation and that often result in undesirable outcome"*.
In this context Impulsivity is an important aspect to consider for evaluating some specific pathologies, but, unfortunately, the evaluation is based on questionnaires. From the definition we can observe that an impulsive behavior or gesture lacks of premeditation, that is, it is performed **without a significant preparation phase**.

A good example of motion analysis for evaluating Impulsivity, is represented by Heiser and colleagues work (Heiser et al., 2004). Using a IR video camera they recorded the motion of young subject with Hyperkinetic Disorders before and after medicine assumption, and they analysed the material with manual annotation and single point tracking. The motion of these subjects has been classified as *"was 3.4 times as far, covered a 3.8-fold greater area, and had a more linear and less complex movement pattern"*, that, for our purposes, can be translate as **linear, without complex pattern**.

Closed to our research area is the analysis of natural gestures conveying information to support verbal communication. In this area there is a well defined taxonomy of gestures in which *Beat Gestures* are similar to impulsive movements. In the Wilson et al. (Wilson et al., 1996) work, beat gestures are defined as *bi-phased* differently from the other gestures (deitic, metaphoric and iconic) that are *tri-phased*. The identified phases are *R (Rest)*, *T (Transition)* and *S (Stroke)*, each one characterized by different execution distance, velocity and magnitude. The phases characterization can be used for the definition and the evaluation of Impulsivity.

An important theory to which refer is the Effort Theory by R. Laban, well resumed by Aliza Shapiro (Shapiro, 1999):
"Effort is the dynamic quality or inner attitude of movement. Laban identified four Effort Qualities in human movement: Flow, Weight, Time, and Space. What this means is that when a person moves, she can be understood to move with some combination of the above qualities. A runner might use Flow and Time. A tap dancer might use Weight and Time. Clearly, there is a variety of ways of tap dancing and of existing in Weight and Time. Each Effort Quality is therefore further refined. Flow consists of a continuum from Bound to Free. Weight Quality consists of a continuum from Strong Pressure to Light. Time consists of a continuum from Sustained to Quick. And Space consists of a continuum from Direct to Multifocused. The poles of these continua are termed elements ".
Using the Effort Qualities we can define the impulsive gesture as a motion characterized by a Time = sudden and a Flow = free.

Resuming what is described above, by integrating different approaches we can define *Impulsivity* as **a short time perturbation of the subject motion state**. Moreover with this multidisciplinary overview we obtain an impulsive gesture characterization that can be resumed as gestures:

- performed without premeditation, i.e. looking to the motion phases with a very short or absent preparation phase.
- performed with a simple pattern, i.e. simple shape performed.
- characterized by a T phase, i.e. short duration and high magnitude.
- performed with Time = sudden and Flow =free in Laban terms.

3 SMOOTHNESS DEFINITION

From English dictionary, *smooth*: *"generally flat or unruffled, as a calm sea; free from or proceeding without abrupt curves, bends, etc.; allowing or having an even, uninterrupted movement or flow"*.

In mathematics, smoothness is linked to the speed of variation, that is, a smooth function is a function that varies "slowly" in time; more precisely, smooth functions are those that have derivatives of all orders. In music smoothness corresponds to articulation in music performance, as for example DiPaola (DiPaola and Arya, 2004) states: *"phrasing of music refers to notes being smoothly connected (legato) or not (staccato) "*.

In psychopathology, smoothness of human movement could allow one to diagnose psychological disorders, for example schizophrenia: patients movements are described "staccato-like, jerky and angular", while they become "smooth and rounded" after successful therapy, as reported in (Wallbott, 1989). As reported in the same study, smooth movements are those:*“characterized distally by large circumference, long waylength, high mean velocity, but not abrupt changes in velocity or acceleration (standard deviations of velocity and acceleration); thus, smooth movements seem to be large in terms of space and exhibit a high but even velocity ”.*

They contrast with “precise, angular, rigid and hasty ”movements. Gallaher (Gallaher, 1992) refers to smooth and fluid movements: *“an individual high on this factor has a smooth voice, flowing speech and gestures, and a fluid walk; such a person would appear graceful and coordinated ”.*

She mainly uses the term smooth when referring to gesture and voice characteristics, while fluid is used for the walking style. Smooth/fluid movements are often associated with slow, sluggish and lethargic movements, in contrast with large and energetic body movement. Slowness in movements corresponds to the definition of smooth functions as slowly varying functions in mathematics.

Wallbott measured displacement of hand in psychiatric patients behavior and found four main movement characteristics: space, which describes the extension of movement; hastiness, which is related to speed and acceleration; intensity, which describes the energy of a movement; fluency-course, which is related to the quality between the beginning and the end of a movement. Wallbott states that smoothness is a possible value for the fluency-course characteristics, thus demonstrating the importance of such parameter in describing movement quality.

The concept of movement smoothness has been studied also in R. Laban’s Theory of Effort (Laban and Lawrence, 1947). In Laban’s model, movement quality is characterized by 4 components: *space*, representing the way in which the movement performer approaches space, in a direct, single-focused way or in a flexible, multi-focused way; *weight*, describing movement impact, that is, whether it expresses less or more energy; *time*, modeling how movement appears, for example suddenly or in a prepared way, lasting a long time; *flow*, expressing the quantity of control the performer has over its movements, e.g., one can fully control its movements or let movement and energy flow through its body freely.

Different movement qualities correspond to different values combinations for the Laban’s parameters: for example *punching* is usually direct, strong and sudden; *floating* is indirect, light and sustained. Smooth movements, as reported in (Newlove, 2007), are usually direct, light, sustained and bound.

4 ALGORITHMS

We now aim to formally define and implement algorithms for extracting impulsivity and smoothness of a human performer in realtime and from a video source.

4.1 Impulsivity

Our aim, after reached the definition, was to develop an algorithm for the automatic evaluation of impulsivity. In this paper we present preliminary results of the algorithm which works in semi-realtime (since this measure can be performed at the end of the gesture and not during the motion). For the gesture identification gesture execution in time we use a motion segmentation based on the Quantity of Motion (Camurri et al., 2004).

The duration of the gesture has to respect the limits highlighted in the definition, i.e. to be “fast”.

In our context the most important factor is the fast attack of the gesture and not only its short duration. In order to quantify the attack we start considering the premeditation and the reaction time. For example in athletics the rules of the International Association of Athletics Federations fixed the minimal reaction time to $0.1sec$ (less is considered a false start), because it considers that the time interval between a sound signal and the voluntary motor activation in a normal subject is around 140-160 milliseconds. Including this consideration in our case, we set the starting phase of a gesture to be faster of a voluntary reaction, i.e. $\leq 0.15sec$. The empirical value we found, during our tests, for the impulsive gesture time duration is $dt = 0.45sec$.

Since we are interested in gestures with “high magnitude ”we considered only gestures with high energy, so the threshold used for the segmentation has been fixed to assume an empirically high value with respect to the standard one.

The impulsive gesture is defined with respect to the current activity, to do this we considered a perturbation as a fast (as above described) modification of the current motion, and we did it by evaluating the usage of the space occupation. With empirically considerations, in order to modify rapidly the actual motion, it is necessary to modify rapidly the posture and in particular to perform a modification of space occupation. For this evaluation we use the variation of the space (Camurri et al., 2004) in the time window of the gesture duration DCI.

The global applied algorithm can then be written as:

let $\triangle t = 0.45sec$;
let gesture $threshold = 0.02$;
if $(energy \geq threshold)$

```
    evaluate the GestureTimeDuration dt;
If dt ≥ 0
    if dt ≤ △t then
        ImpulsivityIndex = △CI/dt;
```

4.2 Smoothness

Research in (Todorov and Jordan, 1998) demonstrates a correspondence between (i) smooth trajectories performed by human arms, (ii) minimization of the third-order derivative of the hand position (called *jerk* in physics) and (iii) correlation between hand trajectory curvature and velocity. In our work we use an approach similar to (iii) to determine if a trajectory is smooth or not starting from the trajectory curvature and velocity.

Let us first explain how the input data is preprocessed: the input to our system consists of video frames frames at 60 Hz showing a moving person. During the preprocessing phase, for each video frame the system extracts the 2D position (x,y) of the barycenter of a green marker placed on the person right or left hand and stores it in a buffer consisting of 60 samples, while the oldest element of the buffer is discarded. The hand position buffer is then provided as input to the smoothness computation algorithm: for every sample (x,y) in the buffer we compute curvature k and velocity v as:

$$k(x,y) = \left|\frac{x'y''-y'x''}{(x'^2+y'^2)^{\frac{3}{2}}}\right| \quad v(x,y) = \sqrt{x'^2+y'^2} \quad (1)$$

where x', y', x'' and y'' are the first and second order derivatives of x and y. To compute them from the buffer of samples (x,y) we apply the Savitzky-Golay filter (Savitzky and Golay, 1964) that provides as output both the filtered signal and an approximation of the $n-th$ order smoothed derivatives. As mentioned above, we define our algorithm for computing smoothness by taking inspiration from (Todorov and Jordan, 1998), that is, we compute correlation between trajectory curvature and velocity. We consider the Pearson correlation coefficient for two variables, that is, in our algorithm, $log(k)$ and $log(v)$:

$$\rho(k,v) = \frac{\sigma_{log(k),log(v)}}{\sigma_{log(k)}\sigma_{log(v)}} \quad (2)$$

However, k and v are computed over a "short" time window, so we could approximate the covariance $\sigma_{log(k),log(v)}$ with 1, as the k and v variate (or not) approximately at the same time:

$$\rho'(k,v) = \frac{1}{\sigma_{log(k)}\sigma_{log(v)}} \quad (3)$$

If we now apply the above steps on the buffer of samples representing the user hand trajectory we could obtain a vector s of real numbers corresponding to the trajectory Smoothness Index:

```
let SmoothnessIndex = empty vector;
for every (x,y) ∈ input buffer of samples
    compute k(x,y), v(x,y) and ρ'(k,v);
    insert ρ'(k,v) in SmoothnessIndex;
endfor
```

5 PILOT EXPERIMENTS & RESULTS

We have conducted preliminary studies inside the EyesWeb developing environment, a system we created to allow researchers and normal users to visually build applications involving multimodal input, computation and output (Camurri et al., 2004). The final aim of these studies will be to determine if our definition of impulsivity and smoothness matches or not the human user perception of these cues. We present preliminary studies in which we mainly test if movements performed intentionally with different impulsivity and smoothness by a human user are classified by our algorithms in the intended way.

5.1 Measuring Impulsivity

Setup and Procedure. The analysis has been applied on bi-dimensional motion performed in front of the video Camera. Subjects are required to perform impulsive gestures after a period of motion or non-motion for cognitive saturation purposes.

The non compressed video signal (60p, 1280x720, BGR) has been processed with EyesWeb software platform to extract the motion features described in Section 4.1. Briefly an algorithm for the background subtraction has been applyed to the video input in order to extract the Silhouette of the subject. From the Silhouette the space occupation and the energy of the motion has been evaluated to identify gestures (see in Figure 1 an example) and to calculate the Impulsivity.

Results and Discussion. The EyesWeb software platform to support the development of real-time multimodal distributed interactive applications. Is a visual environment with predefined sw modules, e.g. for the real-time evaluation of low level motion feature. Using this platform, we implemented the proposed formula and perfomed some tests. In Figure 2 is represented a snapshot of the real-time extraction of the Impulsivity Index. At this stage of our experiment

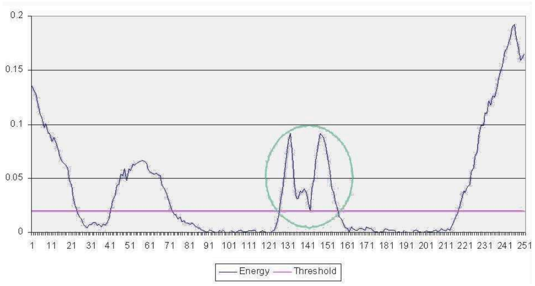

Figure 1: This is an off line representation of the energy motion feature with respect to the threshold value. In the green circle there is the motion bell related to the impulsive gesture. It is important to notice that the motion bell of this gesture, is isolated with respect to the other bells, i.e. is a perturbation of the current state.

the index gives an indication of the performed gesture at the end of the execution because it needs to know the time duration of the gesture.

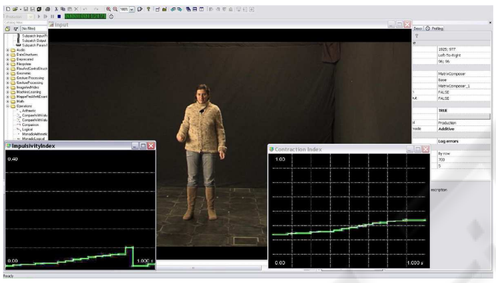

Figure 2: This is a snapshot of the software platform during a real-time evaluation. The Impulsivity Index, in the bottom left part of the image, reach its maximum at the end of the gesture. On the bottom right part of the image there is the related Contraction Index graph, that measure the posture modifications. In the centre there is the current view of the camera.

Results show that our algorithm is able to identify an impulsive gesture, following the definition of Section 2, given a high value of the Impulsivity Index. The quantification of this high value has to been refine, at this moment the impulsive gestures are identify by the Impulsivity Index maximum.

5.2 Measuring Smoothness

Setup and Procedure. With this experiment we aim to verify whether the algorithm presented in Section 4.2 is able to recognize movements performed in a smooth way. As a preliminary test we instructed the performer to produce movements with the following intentions: *(A)* a circular movement, trying to be as smooth as possible, that is, by maintaining a constant speed and curvature; *(B)* a squared movement, produced by performing sharp direction variations in the square vertices; *(C)* a linear horizontal movement, performed by maintaining a constant speed; *(D)* a linear horizontal movement presenting interruptions.
That is, movements A and C presented a high level of smoothness while movements B and D presented sharp variations and segmentation, thus they are not smooth. This is the way we expected our algorithm classifying these four movements.

Results and Discussion. Results of this preliminary study are reported in Figures 3 and 4, corresponding respectively to movements A and B and movements C and D described in the previous Section. The upper part of each Figure shows the trajectories of the performer hand: continuous line represents smooth movements (constant speed) while segments and dots represent movements with sharp direction variations or segmentation. The bottom part of Figures reports the information provided as output by our system EyesWeb in realtime: the trajectory as it was detected by the program and the trajectory Smoothness Index computed between $log(k)$ and $log(v)$, as described in Section 4.2.

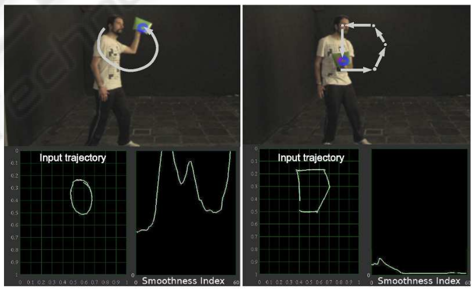

Figure 3: Circular and square trajectories: Smoothness Index is high when computed on the circular smooth trajectory (left) and is approximately zero when computed on the square non-continuous one (right).

Results show that our algorithm is able to distinguish between movements performed smoothly and movements performed with sharp direction variations. As we expected the first class of movements (A and C) present a high Pearson coefficient while for the second class of movements (B and D) the coefficient drops to approximately zero. Of course, these preliminary results do not demonstrate the correctness of our algorithm and further more sophisticated tests should be performed in future.

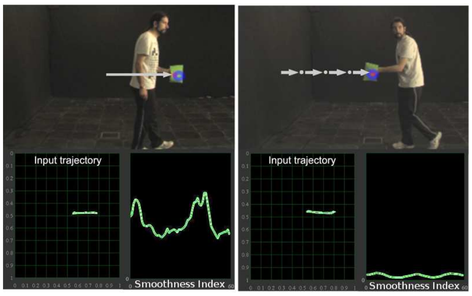

Figure 4: Linear trajectories: Smoothness Index is high when movement is smooth and continuous (left) and is low when computed on the interrupted movement (right).

6 CONCLUSIONS

Improving human computer interaction by detecting the user emotional state is a relevant research topic. Humanistic research shows the possibility to identify emotional states by analyzing body motion feature. The work presented in this paper aims to develop algorithms to measure two motion features: impulsivity and smoothness. In the paper we described the definitions of these two features, the algorithms to evaluate them in real time and the methods we developed to test them.

Future improvements will be designed after new experimental sessions, using both recorded and live performances. Initially we plan to test our algorithms on a video corpus consisting of several gestures recorded in our lab. The gestures are performed by student and professional dancers, and martial art experts. All the videos included in this corpus have been annotated and rated by experts. These ratings will guide us in tuning and refining our methodology. The refined algorithms will then be applied in live performances combined with the extraction of other motion features we already implemented and validated (for example Quantity of Motion and Contraction Index) in order to detect the performer emotional intention. At the same time, we plan to continue validating our algorithms by asking subjects to rate the video corpus described above. Performed and future work are addressed in the framework of the EUICT Project SAME (www.sameproject.eu) and the EU Culture 2007 project CoMeDiA (www.comedia.eu.org).

REFERENCES

Camurri, A., Mazzarino, B., and Volpe, G. (2004). Analysis of expressive gesture: The eyes web expressive gesture processing library. *Lecture notes in computer science*.

DiPaola, S. and Arya, A. (2004). Affective communication remapping in musicface system. In *Electronic Imaging & Visual Arts*.

Gallaher, P. E. (1992). Individual differences in nonverbal behavior: Dimensions of style. *Journal of Personality and Social Psychology*, 63(1):133–145.

Hashimoto, S. (1997). Kansei as the third target of information processing and related topics in japan. In *Proceedings of the International Workshop on KANSEI: The technology of emotion*, pages 101–104.

Heiser, P., Frey, J., Smidt, J., Sommerlad, C., M.Wehmeier, P., J.Hebebrand, and Remschmidt, H. (2004). Objective measurement of hyperactivity, impulsivity, and inattention in children with hyperkinetic disorders before and after treatment with methylphenidate. *European Child & Adolescent Psychiatry*, 13(2):100–104.

Laban, R. and Lawrence, F. C. (1947). *Effort*. Macdonald & Evans, USA.

Newlove, J. (2007). *Laban for Actors and Dancers: Putting Laban's Movement Theory Into Practice : a Step-by-step Guide*. Nick Hern Books, UK.

Picard, R. (1997). *Affective Computing*. MIT Press.

Savitzky, A. and Golay, M. J. E. (1964). Smoothing and differentiation of data by simplified least squares procedures. *Analytical chemistry*, 36(8):1627–1639.

Shapiro, A. I. (1999). *The Movement Phrase and its clinical value in Dance/Movement Therapy*. PhD thesis, Master of Arts in Dance/Movement Therapy, MCP-Hahnemann University.

Todorov, E. and Jordan, M. I. (1998). Smoothness maximization along a predefined path accurately predicts the speed profiles of complex arm movements. *Journal of Neurophysiology*, 80(2):696–714.

Wallbott, H. G. (1989). Movement quality changes in psychopathological disorders. *Normalities and Abnormalities in Human Movement. Medicine and Sport Science*, 29:128–146.

Wallbott, H. G. (1998). Bodily expression of emotion. *European Journal of Social Psychology*, 28:879–896.

Wallbott, H. G. and Scherer, K. R. (1986). Cues and channels in emotion recognition. *Journal of Personality and Social Psychology*, 51(4):690–699.

Wilson, A., Bobick, A., and Cassell, J. (1996). Recovering the temporal structure of natural gesture. In *Proc. of the Second Intern. Conf. on Automatic Face and Gesture Recognition*.

Zeng, Z., Pantic, M., Roisman, G., and Huang, T. (2009). A survey of affect recognition methods: audio, visual and spontaneous expressions. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 31(1).