Automated Detection of Impulsive Movements in HCI

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ABSTRACT

This paper introduces an algorithm for automatically measuring *impulsivity.* This can be used as a major expressive movement feature in the development of systems for real-time analysis of emotion expression from human full-body movement, a research area which has received increased attention in the affective computing community. In particular, our algorithm is developed in the framework of the EU-H2020-ICT Project DANCE aiming at investigating techniques for sensory substitution in blind people, in order to enable perception of and participation in non-verbal, artistic whole-body experiences. The algorithm was tested by applying it to a reference archive of short dance performances. The archive includes a collection of both impulsive and fluid movements. Results show that our algorithm can reliably distinguish impulsive vs. sudden performances.

CCS Concepts

•Human-centered computing → *User models;* **•Applied computing → Performing arts;**

Keywords

full-body movement analysis, dance, impulsivity

1. INTRODUCTION

This paper introduces an algorithm for automatically measuring an expressive movement feature: *impulsivity.* Impulsivity is an important component of emotion expression. According to Loewenstein and Lerner [8], "people commonly display impulsive behavior when they are hungry, thirsty, sexually aroused, or in elevated emotional states such as anger or fear". In psychology, impulsivity is a multifactorial construct [4], which includes at least two independent components: (i) acting without an appropriate amount of deliberation [3] and, (ii) choosing short-term gains over long-term ones [10]. Impulsivity is an important component of various disorders, including e.g., substance use disorders, bipolar disorder, antisocial personality disorder, and so on. In dance, an impulsive movement can be characterized as, according to Bishko, "A movement of increasing intensity ending with an accent is considered impactive. An accent leading to decreasing intensity is impulsive" [1]. At the moment impulsive behavior is detected using questionnaires mainly. For example, the Barratt Impulsiveness Scale (BIS) is one of the most widely used measures of impulsive personality traits. Heiser and colleagues [5] made objective measurements of impulsivity in children with hyperkinetic disorders using an infrared motion analysis system combined with a continuous performance test.

Our impulsivity algorithm is developed in the framework of the EU-H2020-ICT Project DANCE (n 645553)[1]. The main objective of DANCE is to investigate techniques for sensory substitution in blind people, to enable perception of and participation in non-verbal, artistic whole-body experiences. The project investigates algorithms for automated measuring of non-verbal bodily expression of emotion for both single users and groups. Interactive sonification techniques will be applied to expressive movement features, to make blind people perceive them. Impulsivity is a major expressive movement feature the DANCE project addresses.

Practical applications of our algorithm, beside the main goals of the DANCE project mentioned above, will be, for example, emotion detection/synthesis in the field of affective computing. Automated detection of impulsivity in a video surveillance system will allow one to identify, for example, dangerous events, during which people produce impulsive movements. Interfaces such as Virtual Agents will be endowed with more refined movement capabilities and improve the way they display emotional states e.g., fear or anger [9].

2. IMPULSIVITY ALGORITHM

We now provide our definition of impulsive movements. To do that, we briefly introduce definitions and concepts from different domains. In Physics, the impulse is defined as the variation of an object's momentum in time. The momentum depends on the object's mass and velocity. So

[1] http://dance.dibris.unige.it

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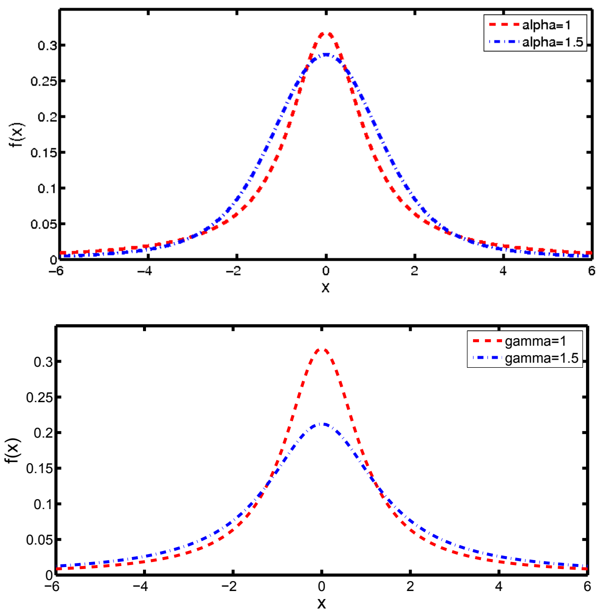

Figure 1: Two examples of probability density functions. In the above one, two functions are displayed, the first obtained by setting $\alpha = 1$ and the second one by setting $\alpha = 1.5$, and leaving the other parameters unchanged. A lower value of α corresponds to thicker pdf tails. The two functions showed in the second plot exhibit γ values of 1 and 1.5.

basically an impulse corresponds to a high variation of the object's speed or, in other words, to high object's acceleration/deceleration. In Acoustics, the impulse is defined as an "*unwanted*, almost instantaneous sharp sounds" [2]. A similar concept can be found in psychological studies, for example in [3]: "actions that are poorly conceived, prematurely expressed". That is, an impulse can be considered as a movement with high acceleration performed with no premeditation. To model this idea, we choose to extract two movement features on which we build our algorithm for impulsive movement detection: *Suddenness* and *Direction Change*. We define impulsivity of movement as the following product, where *Suddenness* and *DirectionChange* are computed as described in the next two sections:

$$Impulsivity = Suddenness * DirectionChange \quad (1)$$

2.1 Suddenness

Alpha-stable distributions have been introduced by [7] and applied in several works on signal processing. They have been exploited as an alternative and more efficient approach than Gaussian distributions to model impulsive noise in [11] or to define a model of graphical textures exhibiting impulsive features that can not be defined via Gaussian distributions [6]. Briefly speaking, an alpha-stable distribution can be modeled by a a probability density function (pdf) characterized by four parameters $(\alpha, \beta, \gamma, \delta)$:

- $\alpha \in (0, 2]$ is the characteristic exponent that defines whether the distribution includes impulses;
- $\beta \in [1, 1]$ is the determines the skewness of the pdf;
- $\gamma > 0$ is the dispersion parameter and corresponds to variance in Gaussian distributions;
- $\delta \in (-\infty, \infty)$ is the shift from the origin of center of the pdf and corresponds to the mean value in Gaussian distributions.

2.1.1 *Suddenness Algorithm*

Algorithm 1 Suddenness

procedure SUDDENNESS($hand\_pos, l$) ▷
  $hand\_pos$: 3D position of right hand ▷
  l: length of time window
  $result.Clear()$
  for each window w of length l **in** $hand\_pos$ **do**
    $vel \leftarrow \emptyset$
    $v_A.Clear()$
    for i **in** w **do**
      $v \leftarrow diff(i)$
      $v_A \leftarrow v_A.Add(\sqrt{v.x^2 + v.y^2 + v.z^2})$
    $[\alpha, \beta, \gamma, \delta] \leftarrow stblfit(v_A)$
    if $\beta < 0$ **then** $result.Add(0)$
    else $result.Add(\gamma * (1 - (\frac{\alpha}{2})))$
  return $result$

We aim to exploit the characteristics of alpha-stable distributions to detect sudden movements. To do that, we implement Algorithm 1. The algorithm takes as input the 3D right hand position of the user and the length of the time window on which the suddenness feature has to be extracted. For each time window containing 3D position of the right hand the algorithm computes the absolute velocity of the hand by differentiating the hand position and computing the module of the vectors resulting form the differentiation process. Then, it applies the $stblfit$ function, that is, a C++ implementation of the stable fit Matlab algorithm[2].
The α parameter, that varies in $(0, 2]$, is scaled and multiplied by γ and the result is stored into variable s. This process implies 2 consequences: (i) when α tends to zero, the scaled value of α tends to one and vice-versa; (ii) movements exhibiting *low* (resp., *high*) velocity will correspond to *low* (resp., *high*) values of γ. That is, s will be high for sudden movements (α low) with large velocity variability (γ high). Also, we check the sign of β: sudden movement exhibiting a fast deceleration of the hand will generate negative values of β; in this case we set the value of s to zero.

2.2 Direction Change

In order to detect impulsive movements we aim to identify actions executed without premeditation. If we focus on hand movement, an *intentional* action, exhibits a *preparation* phase, that is, a phase during which antagonist muscles are charged before the actual movement is performed; instead, *unintentional* movements are performed without preparation. We can detect such kind of actions by estimating movement direction: if preparation phase is performed then the hand moves first in the opposite direction of the actual movement. In this case we say that direction of movement *does not change*. Algorithm 2 performs the computation of direction change, returning zero if the hand moves

[2]http://www.mathworks.com/matlabcentral/fileexchange/37514-stbl--alpha-stable-distributions-for-matlab

in the same direction, a value in $(0, 1]$ otherwise, where 1 means that hand moves on a trajectory exhibiting a change of direction of 90 degrees.

Algorithm 2 DirectionChange

procedure DIRECTIONCHANGE($hand\_pos, \Delta t, \epsilon$) ▷ *hand_pos*: 3D position of right hand ▷ ϵ: tolerance factor
  $result.Clear()$
  for $t = 2\Delta t$ **to** $hand\_pos.Length()$ **do**
    $p_0 \leftarrow hand\_pos(t)$
    $p_1 \leftarrow hand\_pos(t - \Delta t)$
    $p_2 \leftarrow hand\_pos(t - 2\Delta t)$
    $L_0 \leftarrow 3DLineFromPoints(p_0, p_1)$
    $L_1 \leftarrow 3DLineFromPoints(p_1, p_2)$
    $a \leftarrow 1 - \frac{AngleBetween(L_0, L_1)}{\pi}$
    if $|a - 0.5| < \epsilon$ **then** $result.Add(1 - \frac{|a-0.5|}{\epsilon})$
    else $result.Add(0)$
  return $result$

The algorithm computes the angle between two lines: (i) the line going from the current user's hand position the user's hand position 0.2 seconds before; (ii) the line going from the user's hand position 0.2 seconds before and the user's hand position 0.4 seconds before. If a movement is prepared, these 2 lines tend to be parallel (i.e., the angle between them is near to either 0 or 180 degrees), otherwise the angle between them approximates 90 degrees. The output of the algorithm will tend to zero in the first case, to one in the second case.

3. EVALUATION

The algorithm presented in Section 2 was tested on a reference archive of short dance performances recorded in the framework of the DANCE project. 18 performances regarding different tasks, lasting about 3 to 4 seconds each, and belonging to 3 different classes, were randomly selected and analyzed: (1) 6 consisting in impulsive movements (e.g., a blind-folded performer was asked to image to be suddenly touched by a hot stick and to react accordingly); (2) 6 consisting in sudden (and prepared) movements (e.g., a performer was asked to punch in front of her); (3) 6 consisting in non-sudden (i.e., *sustained*) movements (e.g., a performer was asked to draw circles in the air). Figure 3.1.2 shows three examples of the execution of our algorithm. In the first column on the left an impulse is detected, since movement is sudden (first panel from top) and direction of movement changes of about 90 degrees (second panel). In the middle column a high velocity but non-sudden (that is, sustained) and repetitive movement is not detected as impulsive. Finally, in the third column, a very sudden movement (second half of the interval in the first panel from top) is not detected as impulsive since direction changes by 180 or 0 degrees.

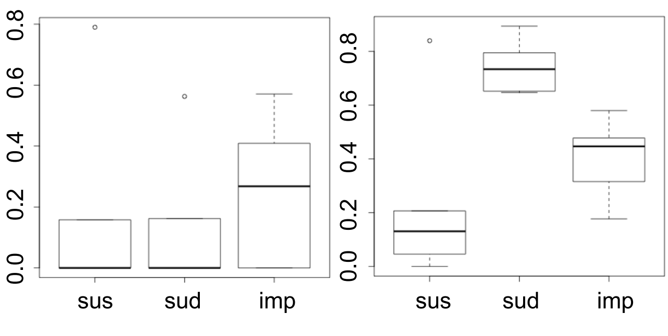

Figure 2: Boxplots of the output of the impulsivity (left side) and suddenness (right side) algorithms for the three classes of performances.

3.1 Results

We provide the results of the computation of the Impulsivity (Equation 1) and the Suddenness (Algorithm 1) on the 18 performances described above. We compute the average within each of the 3 classes of the maximum values the two algorithms produced for the 6 performances belonging to each class.

3.1.1 Impulsivity Algorithm

Left side of Figure 2 shows the boxplots of the outputs of the Impulsivity algorithm. A Shapiro-Wilk test revealed that data was not normally distributed ($p < 0.05$ for two over the three classes), so a Kruskal-Wallis test was used to compare the output of the impulsivity algorithm between the three classes of performances. Even if the boxplots display that the average output value for the impulsive performances is bigger than those for the sudden and sustained performances, the statistical test did not reach significance ($p = 0.52$). This may be due to the small sample size and to the fact that the output of the impulsivity algorithm is zero for most of the sudden and sustained performances.

3.1.2 Suddenness Algorithm

Right side of Figure 2 shows the boxplots of the outputs of the Suddenness algorithm. A Shapiro-Wilk test revealed that data was not normally distributed for one over the three classes ($p = 0.01$). Further, a Bartlett test of homogeneity of variances showed that variances are not homogeneous ($p = 0.03$). So a Kruskal-Wallis test was used to compare the output of the suddenness algorithm between the three classes of performances. Results show that the difference is significant ($H = 9.0877$, $d.f. = 2$, $p = 0.01$). A Dunn's test was then used to make post-hoc comparisons. A Bonferroni correction was applied to account for multiple comparisons. Results show a significant difference in the output of the suddenness algorithm for the sudden and sustained performances ($p = 0.005$). The difference for sudden and impulsive performances approaches significance ($p = 0.052$).

3.2 Discussion

Even if the results of our evaluation study are very preliminary (due to the very small number of samples), they demonstrate that impulsivity can be successfully detected from human movement data. Suddenness of movement can be detected with a significantly high rate. Starting from the above results a larger evaluation study will be conducted in the framework of the DANCE Project. Samples will include not only impulsive Vs. non-impulsive movements but also movements of multiple dancers.

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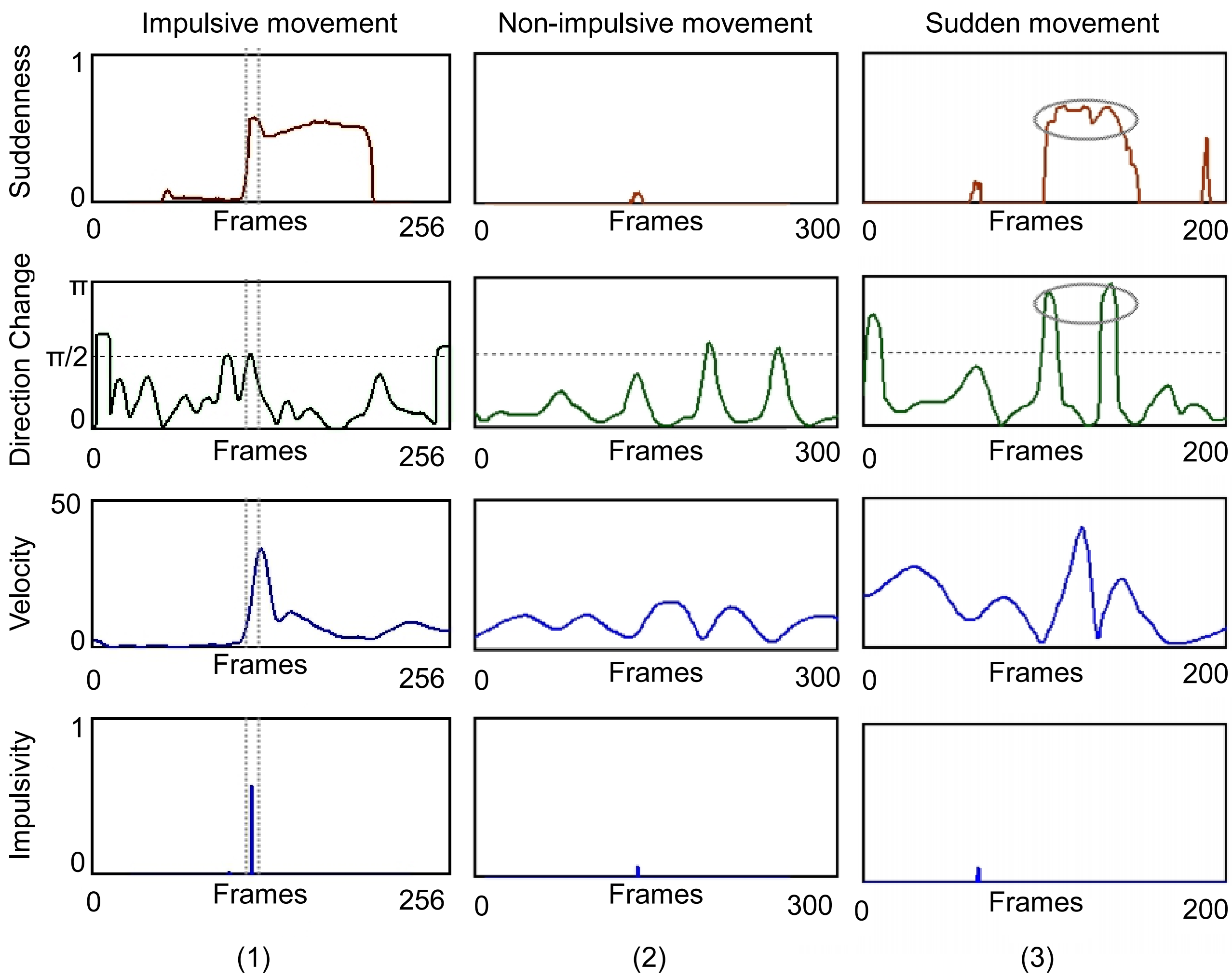

Figure 3: Three examples of the execution of our algorithm, from left to right: (1) an impulse is detected, as movement is sudden (first panel from top) and direction of movement changes of about 90 degrees (second panel); (2) a high velocity but sustained and repetitive movement is not detected as impulsive; (3) a very sudden movement (second half of the interval in the first panel from top) is not detected as impulsive since direction changes by 180 or 0 degrees (second half of the interval in the second panel from top).

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