Directed Effort
A Generic Measurand for Higher Level Behavior Analysis

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Abstract: Behavior and body language are essential components of human interaction. In this paper, we propose a meta-level representation of human behavior for interpretative, higher level applications in human-computer interaction systems called Directed Effort. A theoretical framework is described which is derived from behavioral and psychological sciences and which is designed to represent the commitment and interest of people towards objects via behavior analysis in real-life scenarios. Directed Effort, a score which allows the interpretation of detected behavior changes is introduced as a generic measurand. Furthermore, a prototypical implementation is documented to show the potential of the computed meta-level description of behavior.

1 INTRODUCTION

Behavior and body language are crucial aspects of any kind of interaction between humans. Besides the pure entropy of information which can be represented bit-wise, it is the subtle indicators like the sarcastic tone of voice, the rolling of the eyes or the impatient tapping of the foot through which we transmit the majority of the information which is necessary to successfully interpret messages. Human interaction is largely based on the meticulous interpretation of meta-information for which, even among humans, experts are rare. This poses an immense challenge to all researchers and designers of human-computer interaction systems that aim at creating natural and intuitive user interfaces, trying to best possible generate a human-like interaction quality experience in human-computer interaction systems.

Human behavior encompasses any observable physical activity. Yet, The description of behavior not only has to cover different aspects of behavior depending on the respective field of application, but can also imply many different layers of abstraction. These can range from a technical analysis of body pose based on joint coordinates and orientations to a higher-level interpretation of body language, or from the pure analysis of movement speed data to an interpretation of underlying motivations and intentions. An ideal representation of behavior will of course include all behavioral aspects and layers, whereas actual applications and implementations will set limitations to what is necessary, useful and technically feasible.

As human interaction is largely based on the interpretation of human behavior, we need to create representations of behavior which allow further interpretations of intentions that go beyond explicit user input. In this work, we try to approach such a potential higher level description which may be applicable to represent human commitment and interest. For this purpose, we propose a generic meta-level description of behavior which is designed to be generally valid, generic, independent from sensor technology, and quantifiable to be suitable for various human-computer interaction applications.

1.1 Related Work

Commitment and behavior have often been approached from different scientific fields which resulted in numerous strategies towards specific aspects and effects related to behavior, commitment and attention. Elaborate surveys on human behavior analysis have been composed by Ji et. al (Ji and Liu, 2010) and Candamo et. al (Candamo et al., 2010).

Concentrating on technical realizations, the implementations can be divided into the already indicated categories of action or acitivity recognition and a semantic representation of behavior. Activity analysis can be covered by template-based or state-

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space-based approaches. Employing templates, Bobick and Davis (Bobick and Davis, 2001) first used *motion energy images* and *motion history images* to represent and categorize activities. Blank et. al (Blank et al., 2005) extracted the 3D silhouette of people to enable a fast and robust classification of activities. State-space approaches interpret human behavior as a state machine with different postures as states. These are often represented via Hidden-Markov-Models (HMMs) (Peursum et al., 2007), (Shi et al., 2006).

Semantic descriptions of behavior have gained momentum lately. The importance of body orientation in human interaction is investigated by Hietanen (Hietanen, 2002) with the result that head and upper body orientation are vital components which nonverbally transfer the aspect of engagement in an interaction. Guevara and Umemuro (Guevara and Umemuro, 2010) implemented a behavior analysis to infer on psychological states, finding that walking velocity and motion load are suitable for predicting sadness or neutral states of mind.

Usually, in human-computer interaction human-computer interaction research, commitment is interpreted as equivalent to visual focus and no further attention model is integrated. Smith et al. (Smith et al., 2006) created a head tracking and gaze estimation system which detects whether passing people are actually watching a shop window. Yakiyama et al. (Yakiyama et al., 2009) estimate commitment levels towards target objects via a laser sensor and on the basis of computed distance, basic orientation and movement speed. According to Knudsen (Knudsen, 2007) orienting movements are used to optimize the resolution of (visual) information about the object.

2 THE CREATION AND CONTROL OF BEHAVIOR

Human behavior addresses any observable physical activity of the individual. To enable a successful interpretation, it is essential to understand basic underlying behavioral mechanisms. This chapter will describe a model derived from psychology and behavior research of how behavior is motivated, controlled and initialized.

Following Bongers (Bongers et al., 2009) and Dijksterhuis (Dijksterhuis and Aarts, 2010), behavior is controlled via a sequential motivation chain (fig. 1): Input stimuli are processed and filtered regarding their value, importance and salience. The successive stimuli compete with already existing *Motivations* for their realization. The result of this competition is a set of prioritized *Goals*, that describe the intrinsic, often unconscious intentions of a person. These cannot be assessed from the outside and may be as simple as 'being hungry', or complex structures which can not be verbalized at all. To actually achieve these abstract *Goals*, we make concrete *Plans* like navigating to the next restaurant, to satisfy the underlying motivation. Finally, the actual realization of these plans leads to the execution of observable physical behavior.

With outward behavior visualizing and representing inner states, a thorough analysis of pyhsical behavior holds great potential for a suitable analyis of the level and even orientation of inner commitment. Elementary changes in the motivation chain, e.g. triggered by sudden extrinsic stimuli (siren, etc.) will cause a sequence of re-prioritization of Goals and Plans and finally result in alterations of physical behavior. Our approach is directed at the observation and interpretation of such behavioral changes, to infer alterations and repriorizations in the unfortunately unobservable motivation chain.

The proposed model correlates very well with existing behavior control findings. Posner (Posner, 1980) investigated the connection between extrinsic behavior, e.g. head turning, eye movements towards selected stimuli and inner processes which describe all completely mental activities. Posner found the relation between covert and overt attention to be not a close but a functional one, showing a 'striking tendency of attention to move to the target prior to an eye movement'. Hoffman (Hoffman and Subramaniam, 1995) showed that, being ordered to direct gaze towards a certain location, one cannot attend objects at a different location. This existence of a neural structural connection between exterior and inner focus was supported by Moore (Moore and Fallah, 2001), Perry (Perry, 2000) and Rizzolatti (Rizzolatti et al., 1987). On the other hand, experiments carried out by Hunt and Kingstone (Hunt and Kingstone, 2003) indicate that in case of bottom-up controlled, reflexive processes overt and covert attention are strongly related whereas for top-down controlled processes, inferring backwards from eye gaze alone to overt attention is error-prone. The difference between reflexive and voluntary controlled mechanisms is supported by Müller and Rabbitt (Müller and Rabbitt, 1989), who detected higher reorientation performances for reflexive reorientation of attentional focus.

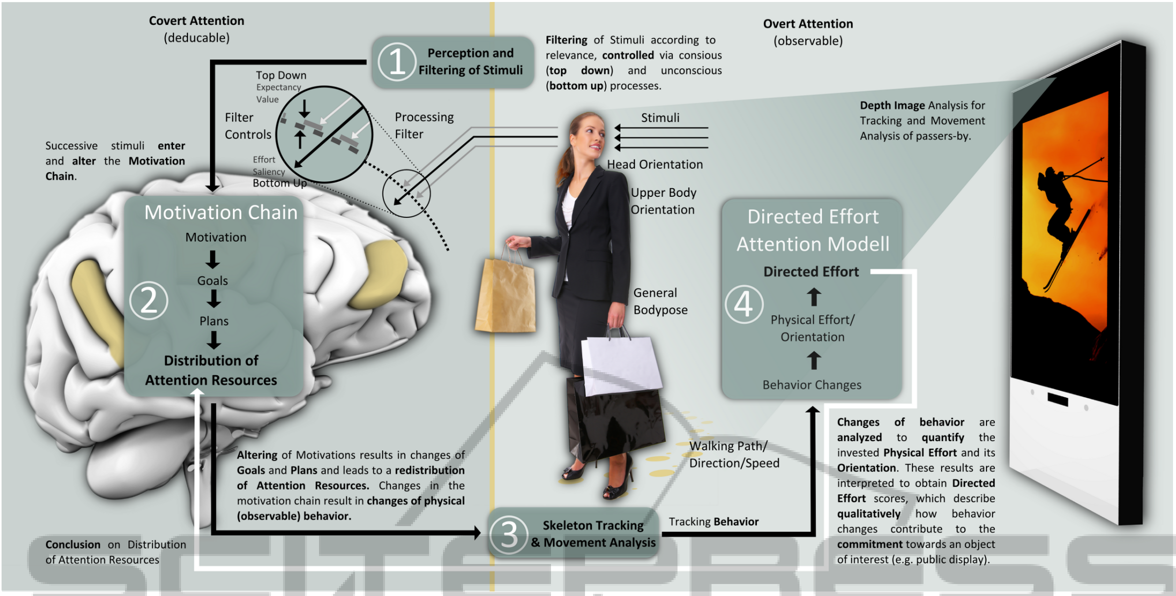


Figure 1: Schematic Illustration of the intrinsic and exterior processes of behavior control. (1) Incoming stimuli are filtered according to top down and bottom up processes (SEEV model (Wickens and McCarley, 2008)) (2) Succeeding stimuli enter and alter the Motivation Chain and influence the distribution of Attention Resources (3) Realization of Plans expresses in observable behavior (4) Behavior changes can be tracked, quantified and interpreted.

3 EFFORT AS KEY-PARAMETER FOR BEHAVIOR ANALYSIS

Having a model of how behavior is generated, the next step is to find a suitable representation which is characteristic for all kinds of behavior and especially describes changes of behavior in a qualitative and quantitative way.

Every alteration of existing plans and accordingly of current behavior is characterized by its demand for a certain amount of *Mental Effort*, which includes the process of filtering stimuli input and deciding to commit to a source of information and consequently a rescheduling of future tasks. Furthermore, it requires *Physical Effort*, '*an important concept, ... required to access different sources of information, using whatever mechanism is necessary: eyes, head, body, hands or even the walking feet*' (Wickens and McCarley, 2008), to actually alter physical behavior.

In this context, the principle of the economy of movement represents a crucial aspect. As Bitgood states: '*To overcome the economy of movement motivation,.. , the perceived benefits of approaching an attractive object must outweigh the perceived cost of the effort*' (Bitgood, 2006). Generally, people tend to optimize their behavior concerning energy consumption and effort, physical or mental, as '*excessive mental effort, like excessive physical effort, generally produces an unpleasant state that is to be avoided. Hence, people tend to be inherently effort conserving, particularly when placed in high demanding environments...*' (Wickens and McCarley, 2008). Consequently, we assume that one will stick to his current comportment until given valid reason to change, thus evading unnecessary investment of effort.

To give an example, in spatial contexts, behavior control is influenced by the effort which is necessary to access information sources. This physical effort involves all overt processes from eye movement, over body posture to movement parameters. Kahneman states that '*because of the connection between effort and arousal, physiological measures of arousal can be used to measure the exertion of effort*' (Kahneman, 1973). According to Knudsen (Knudsen, 2007) Orienting Movements are used to optimize the resolution of (visual) information about the object. To demonstrate these principles, a sample scenario of a person moving through a shopping mall is displayed in figure 2. Passing a public display, there are different behaviors that can be adopted. In the sample scenario, the described options (a)-(c) differ in the amount of energy and time which are invested to engage with the display and the presented content. As can be observed, the more effort is invested the higher will be the commitment to the object.

Bringing it all together as illustrated in figure 1, in the complete process of (i) filtering stimuli, over (ii) alteration of the motivation chain to the (iii) allocation

Figure 2: Different kinds of behavior in a mall scenario when passing a public display. (a, white) Passers-by may not perceive the display at all and show no reaction, (b, yellow) turn their head towards the screen but continuing current general behavior of approaching their destination or (c, green) actually changing the path, investing time and commitment in perceiving the presented information.

of attention resources and finally to the (iv) execution of related plans to satisfy underlying motivations, it is named Effort which represents the critical threshold of whether attention resources are assigned and behavior is changed. At the same time it represents an observable indicator of physical commitment to a source of information. With effort being (not the only but) such an important regulating factor in behavior control, we propose physical effort as the basis for a generic and generally applicable higher level representation of behavior.

4 BEHAVIOR ANALYSIS FRAMEWORK

Providing a valid measurement of behavior, demands three important elements: (a) measuring directly significant target behavior, (b) measuring a relevant dimension of target behavior and (c) ensuring that the data is representative for the given use-case (Cooper et al., 2007). In this chapter, a behavior measure framework is proposed based on interpreting behavioral changes which tries to best possibly match these prerequisites.

To approach an actual implementation, changes of behavior need to be detected, quantified and evaluated. We assume an interaction system with any kind and number of sensor-based tracking system(s) (cameras, distance sensors, depth sensors, etc.) with which behavioral data can be collected. The collected behavior data depends on the choice of sensor and application scenario and may include any measurable data that describes movement in a characteristic way like skeleton joint coordinates, gaze direction, etc.

Our proposed framework (fig. 3) defines four important variables, which are behavioral parameters $b_i(t)$, Effort $e_i(t)$, Effect $f_i(t)$ and Directed Effort $DE(t)$.

$$b_i(t) = s(i,t) \tag{1}$$

$$e_i(t) = \Delta(b_i(t), B_i(t_0; t-1))) \tag{2}$$

$$f_i(t) = \Phi(b_i(t), \vec{x}) \tag{3}$$

$$DE(t) = \sum \alpha_i \cdot e_i(t) \cdot f_i(t) \tag{4}$$

Behavior parameters b_i (equ. 1) describe the sensor data $s(t)$ extracted to exclusively describe a single aspect of behavior i. These could range from movement speed, orientation or location of single body joints to a emitted volume of whole groups of people. The selection of these behavioral features heavily depends on the application and choice of sensor. For later evaluation of the data, it is necessary to best possible isolate the characteristic parameters of the aspired behavior parameter in the feature extraction process. Please note, the behavior parameters may range from mere numeric to directed dimensions like vectors, angles, etc. Due to this variety, the notation has been confined to an abstract placeholder b_i.

The extracted behavior data is used to calculate changes in behavior individually for each behavior parameter per frame t. For this purpose, training data B_i is collected to describe recent reference behavior which is used to detect the amount of alterations. The process of calculating the amount of effort $e_i(t)$ which is required to execute the detected change of behavior (equ. 2) is represented via Δ (equ. 5). In this function, effort is represented via a percental represen-

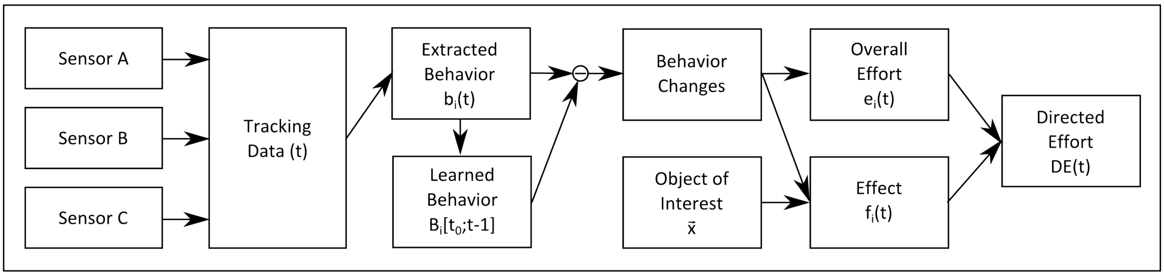


Figure 3: Visualization of behavior analysis framework components. Tracking data is collected from sensor(s). Feature extraction algorithms provide behavior data which is used to calculate reference behavior and current behavior changes. The changes of behavior are processed to effort scores and evaluated in relation to the location of the object of interest to obtain effect information. Finally, effort and effect are combined to a single expressive feature called Directed Effort which describes the level of engagement of behavior changes to an object of interest.

tation in relation to the maximal possible change of behavior for the respective behavior parameter. E.g., turning the head with an angle of 20° and assuming a maximum turn of 180° would result in an effort of $20^\circ/180^\circ = 11,1\%$ for the behavioral parameter of head turn. In spite of the issue of defining these maximum values, this process provides a normalized level of effort scores throughout completely unrelated parameters of behavior, making them comparable.

$$\Delta(b_i(t), B_i[t_0; t-1]) = \frac{b_i(t) - B_i(t)}{b_{i,max}} \qquad (5)$$

These effort scores e_i represent the overall and unevaluated invested effort scores. Accumulating over i would deliver the overall amount of invested effort. Yet, the proposed isolated representation of the effort per behavior parameter is necessary for the following evaluation of the orientation and effect of the invested effort. Assuming that all behavior changes are causally determined, our approach tries to interpret the effect of the detected behavior to deduce the source of the behavioral change and thus draw conclusions on the underlying motivations.

Given the vast amount of potential objects of interest and the high possibility that the actual sources of the behavior change are unknown and outside of the observable area, the evaluation has to be restricted to distinct objects. This restriction will not allow a general identification of sources of interest but at least enables the observation and evaluation of distinct, single targets. By defining the location $\vec{x}$ of an object of interest (OOI) in the observed scene, it is possible to analyze the effect f_i of the change on potential commitment to this OOI. The evaluation of the behavior data (equ. 3) in relation to the location of a reference OOI is represented by Φ (equ. 6). Again, this function needs to be accustomed to the specific behavior parameter and a percental representation is proposed.

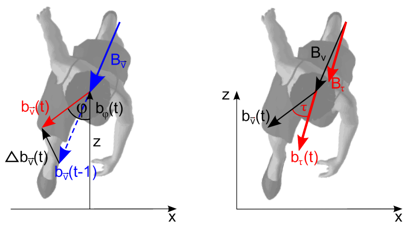
$$\Phi(e_i(t), \vec{x}) = \frac{\vec{b_i}\,(t, \vec{x})}{b_{i,opt}} \qquad (6)$$

As a final step, extracted information concerning the amount and the effect of the invested Physical Effort are combined into a single expressive value called *Directed Effort* (equ. 4) which represents the effective invested Effort which is has been evaluated as contributive regarding potential OOI. In other words, Directed Effort scores describe how much effort which is directed at a specific object, has been invested. The already calculated values $e_i(t)$ and $f_i(t)$ hold the amount and effect of the respective behavior parameters i. To combine them to a single expressive score, the products of the corresponding effort and effect scores are accumulated and weighted with a factor α_i. This weighting again depends on the application scenario and choice of parameters. By interpreting these Direct Effort scores, we hope to be able to draw conclusions on the distribution of attention resources which has evoked the observed behavior.

5 EXEMPLARY IMPLEMENTATION

To demonstrate the functionality of the proposed framework, a sample implementation is described in the following. A public display scenario has been selected, in which the commitment of passers-by to the displayed content is supposed to be investigated. To enable behavior analysis, a large-scale public display has been equipped with a depth sensor which allows an accurate tracking of body pose and extraction of movement features of passers-by.

First, the aspired behavior parameters b_i need to be identified and defined. In the given scenario, behavior can be unraveled into the three existing degrees



(a) (b)

Figure 4: (a) Visualization of behavior parameters b_v, b_φ and (b) b_τ.

of freedom of movement which are *movement direction*, *body orientation* and *velocity*.

Body orientation is set identical to head orientation, as it turned out to be the orientation component of the highest relevance and the best tracking results in our implementation. The effort component which derives from movement direction and body orientation is calculated as the difference of the detected current angles b_τ and b_φ (fig. 4) to learned current reference values B_τ and B_φ. In this application, the 'learned' components B_i are implemented as an exponentially decreasing low-pass filter (equ. 10). Finally the alteration is set in relation to the maximum change per parameter, which are $\pm 180°$ for movement direction and $\pm 90°$ for head orientation.

To calculate the effort invested in a change of speed, acceleration values b_v can be analyzed. Yet, here a different approach is followed, since relation to a theoretical maximal acceleration value does not adequately describe real circumstances. In this case, an acceleration from $5\frac{m}{s}$ to $10\frac{m}{s}$ would result in the same effort as an increase from $15\frac{m}{s}$ to $20\frac{m}{s}$, although in the first case the speed has been doubled. This is why a different percentaged representation has been chosen which describes the percentaged change in relation to recent velocity. Note, that only effort from behavior changes are analyzed at this point, although of course, maintaining a high speed will involve immense physical effort. The inclusion of these constant aspects of effort are part of current research for the generalization and enlargement of the framework.

$$e_v(t) = \frac{b_v(t)}{B_v} \tag{7}$$

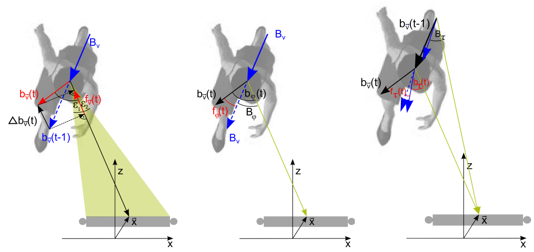
$$e_\varphi(t) = \frac{\left|\left(b_\varphi(t) - B_\varphi\right)\right|}{90} \tag{8}$$

$$e_\tau(t) = \frac{|e_\tau(t)| - B_\tau}{180} \tag{9}$$

$$B_i = \frac{1}{30} \cdot \sum_{n=0}^{30} \frac{1}{n} \cdot b_i(t-n) \tag{10}$$

To analyze the effect of the invested effort towards the display location, the orientation of the behavioral changes has to be evaluated in relation to the location of the display, which results in a measure of the contributivity of the detected activities to the display location. E.g. a person making a turn of 90° will always result in the same detected physical effort no matter where in the scene the activity took place. But is the interpretation of the orientation towards the display which elevates the detected physical effort from a pure mathematical description of activity to an expressive representation of potential commitment, which is Directed Effort. It enables us to interpret whether activities are directed towards or away from the display, bringing the person to a more or less attentive state.

To evaluate the acceleration parameter $b_v(t)$ (fig. 5(a)) a rule-based evaluation function ϕ_v is selected. First, the absolute effective fraction of the acceleration vector $\vec{a}$ to the display location is analyzed to evaluate to what degree the activity is related to the display. Second, a rule-based evaluation of the contributivity is applied which relies on the assumption that any activity which increases the stay in the range of the display or improves the perception of the display is considered as contributive. Hence, all deceleration and movement into the display sector are interpreted as positive effect, whereas all accelerations which are directed away from the display are evaluated as negative effect (equ. 13).



(a) (b) (c)

Figure 5: Computation of the Effect of (a) the acceleration $\Delta b_{\vec{v}}(t)$ by computing the component of $f_{\vec{v}}(t)$ that is directed at the object (orthogonal projection of $\Delta b_{\vec{v}}(t)$ onto the direct connection to the object location), (b) $b_\varphi(t)$ by the change of movement angle towards the object and (c) $b_\tau(t)$ by change of orientation angle $f_\tau(t)$ towards the object.

$$\Phi_v(t, \vec{x}) = \rho_v(t) \cdot b_{v,f}(t) \tag{11}$$

$$b_{v,x}(t) = \frac{\vec{x} \bullet \overrightarrow{b_v(t)}}{|\vec{x}|^2} \cdot \vec{x} \tag{12}$$

$$\rho_v(t) = \begin{cases} 1, & \text{if } b_v(t) < 0 \ \ || \ \omega[t] \ \leq \varepsilon_1, \varepsilon_2, \\ -1, & \text{else.} \end{cases} \tag{13}$$

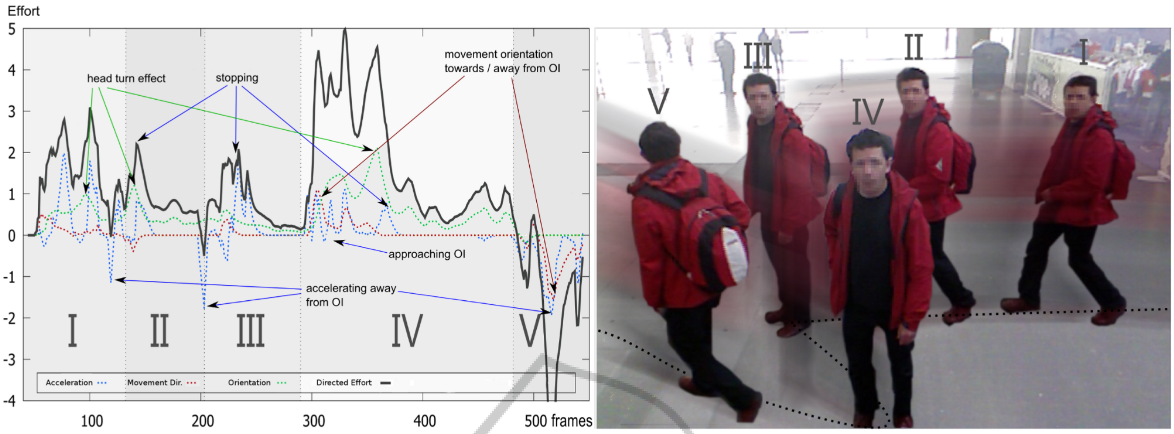


Figure 6: Directed Effort Scores plotted over time with corresponding behavior illustration. The scene is divided into phases (I-V). (I): Person walking parallel to display with head turned towards the screen. (II) and (III) Person stopping to watch, movement direction still parallel and head turned. (IV) Person approaching the screen changing direction assuming a close and comfortable position with head and shoulders oriented in the same direction. (V) Turning and leaving the scene. The dotted curves show the result for the single components of Directed Effort which are aggregated to an overall score of Directed Effort (solid line). Positive amplitudes express positive contributions, negative amplitudes indicate activities which are directed away from the display.

Considering the effect of variations in movement direction and orientation, changes are considered beneficial, if the movement causes the angle towards the display location to decrease (equs. 14, 15). Again, the effect scores are percentaged in relation to the maximal value.

$$\Phi_f(t) = \frac{(B_{\varphi,x} - b_{\varphi,x}(t))}{180} \tag{14}$$

$$\Phi_\tau(t) = \frac{(B_{\tau,x} - b_{\tau,x}(t))}{180} \tag{15}$$

$$DE = \sum_i \alpha_i \cdot e_i(t) \cdot f_i(t) \tag{16}$$

Bringing it all together, the effort and effect scores are weighted with parameters α_i and accumulated to the final Directed Effort score. The weighting parameters are necessary to achieve realistic, well-balanced effort scores. They have to be established during a test phase of the system for each application.

Referring to the stated requirement from chapter 4, it can be summarized, that the framework and the exemplary implementation can claim to fulfill the specifications. The described behavior measurement procedure directly measures significant behavior in a useful dimension and works on data from real life scenarios.

6 RESULTS

To evaluate the framework functionality, plotting DE scores over time provides useful information. It results in effort curves which are useful to present the applicability and the potential of our effort-based behavior analysis approach. The resulting curves succeed in adequately describing behavior and signal changes of behavior via strong signal peaks. In figure 6, the effort curves have been plotted for the single DE parameters acceleration, moving direction, and shoulder and head orientation which contribute to the overall Directed Effort curve, using an example from a database which was gathered during an installation at a public event. This sample has been divided into five sections which mark different behavioral segments.

As can be observed, the calculated DE curve gives a suitable expression of invested physical effort and enables detection and interpretation of behavioral changes. The beginning of each of the sections which indicate different kinds of activities is marked with a strong peak in the DE curve, indicating a high effort level and a substantial change in behavior as demanded in our theoretical approach. The height and width of the peak represent an indicator for the strength of the behavior modification and the algebraic sign clearly separates contributive from detrimental actions. Smaller behavioral changes like the deceleration in sections II and III result in a lower peaks than changes which include strong deviations in in more than one of the single parameters, as in section IV and V. In the latter sections, the person not only alters movement speed, but as well the movement direction and body orientation resulting in higher DE scores.

The noise-like patterns which occur throughout the sample are mainly caused by oscillations in the acceleration parameter, which derive from the gait frequency and the slightly strolling walking style of the subject. Overall, DE curves show promising stability and at the same time reactivity to behavior modifications and seem to adequately describe the qualitative commitment of people towards objects like public displays.

7 CONCLUSIONS AND OUTLOOK

In this paper, we have presented an approach towards a higher level interpretative description of behavior to express engagement and commitment of via detection of behavior changes. Such an approach can never claim to be able to predict the exact focus of attention of a person but can only try to provide a model which approximates reality through iterative refinement. The more we accomplish a detailed description of behavior and context, the better we will perform in interpreting human behavior. Yet, the proposed methods may provide a first step towards a behavior-based attention estimation.

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