What Can Body Movement Tell Us About Players' Engagement?

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Introduction

With the advent of full-body technology, we are witnessing a growing interest in the role played by the body in shaping and also measuring experiences [1]. There are three main reasons for this. First, the emergence of multimodal technology has brought our body back to the centre of the interactive experience. Second, the availability of increasingly cheaper and unobtrusive motion capture sensors allows for a more feasible analysis of continuous behaviour. Third, an increasing understanding, from various research fields, of the fact that body movement and posture affect the way we perceive and evaluate both ourselves and the environment (e.g. [2, 3]), raises new interesting and challenging questions regarding measuring engagement.

According to the pragmatist philosopher John Dewey and to embodied interaction research [4, 5, 6], experience is not predefined by the design of technology. Rather, it emerges through the interaction between user and technology within a context where the body is a vehicle for engagement. This has led HCI and game researchers to investigate more thoroughly the role of body movement in player experience [7-10]. In [7], the author proposes a taxonomy of movements that is important to player experience and lets the players appropriate the game, i.e. actively construct meanings of their own game experience. In this paper, we use this taxonomy and the studies reported in [7, 12, 13] to suggest body movement measures to gain insight into the player's engagement.

Body movement as a measure of commitment to gameplay

According to the taxonomy proposed in [7], there are two types of body movements that are related to the performance of the game: task-control movements and task-facilitating movements. Task-control movements are the movements set by a game designer for the control of the game. Task-facilitating movements are movements that players use to facilitate the control of the game (i.e. distributed cognition over body resources available [14, 15]). Since coordinating available resources requires knowledge about the activity (i.e. the game), these types of body movements are generally used only by experienced players [14].

What should we measure of these two categories of movements? In [12] and [13], the authors found that players appropriated the controllers, and hence the body movements to control the game, according to the motivations that led them to play the game. When they were led by wanting a hard-fun type of game (i.e. challenging their skills to win the game), players reported using their body movements to exploit optimally the functionalities offered by the controller to gain points. Hence, a first measure of engagement should provide a measure of the player's effort to optimize the control of the game. Four consecutive phases could be envisaged as part of this optimization process: exploration, consolidation, mastering and performing.

During the exploration phase, the player is engaged in understanding what the control movements are and how their body can accomplish them. A body-pattern-entropy measure could be used to detect these explorative phases. This measure could be computed for different body parts or groups of body parts. Investigating the profile of these measures over time could provide insights into the effort and progress of the players. It could be expected that, rather than decreasing over time, their profile may be characterized by multiple local minima (each corresponding to the learning of a particular body movement pattern), until certain body patterns are acquired. If a player remains in a local minimum for too long and his/her task-control movements are still far from optimal, boredom or frustration may appear and the player may disengage. When a set of coordinated task-control movements has been learnt, i.e. their distance from their optimal execution is below a certain threshold, their consolidation phase may start. In this phase, we may expect that the measure of body pattern entropy may increase only on the body parts involved in the type of patterns to consolidate. A measure of distance between the executed movement and the optimal target movement, together with a measure, over time, of the tuning exploration space, could be used to capture the player's effort towards achieving his/her goal.

The phase of mastering may see the emergence of task-related movements (e.g. involvement of other body parts) to further optimize the learnt control patterns. Differently from the explorative phases, where various body parts may be involved without really contributing to the game control, the task-related body movements should be aligned (e.g. in synchrony, or sequentially organized) with the task-control body movements. For example, in [7], the rhythm of foot tapping (task-related movement) is synchronized with the pressing of the guitar buttons (task-control movement) in the Guitar Hero music game [7]. Hence, measures of relatedness between task-control body movements and emerging body movements may be used to detect the players' engagement in appropriating the game and creating their own body movement strategies. Finally, during the performing phase, the player is using the acquired body patterns to win the game. We should expect low entropy at this stage and a variety of task-control movements being exploited.

Whilst we have presented these four phases as consecutive and fully independent phases, we may in fact expect that they overlap as the learning of each different movement pattern may not start at the same time. Also, as the players get better, they may take on new challenges and hence a new learning process may start.

Creation and steering of the interactive game experience.

An important aspect of the player experience is the way the player continuously builds and assigns meaning to the interaction within the game. The studies reported in [7] show that, through proprioceptive feedback, body movement plays a key role in facilitating a transition from a pure hard-fun engagement, where the players' motivations are mainly to win and challenge themselves, to an experience that grounds its pleasure in taking up the role-play that the game offers. Particularly important in facilitating this shift are role-play body movements.

When easy fun and emotional experience motivated play, players fully engaged with and gained pleasure from their body movements, even when these interfered with scoring points [7, 16]. Hence, optimal control of the game may not always be what players look forward to; what players may be working towards is to achieve enjoyable role-play movements. Automatic recognition of role-play body movements may be necessary to measure automatically such types of engagement. The increasing availability of data captured using new movement sensing technologies (e.g. CHALEARN Gesture Challenge[1]) is providing the space and the resources for such capabilities to be developed and we are assisting with a steady progress in this direction [17-22].

Another source of information on the engagement of the players is provided by their affective and social body expressions. Various efforts have been made to create software that can automatically recognize such expressions [11], with increasing interest in naturalistic expressions. For example, [23, 24] have investigated this question in the whole-body game context with promising results. The recognition of these expressions not only informs us of how the player feels but also about the player's motivations for playing the game. In fact, hard fun and easy fun are generally characterized by a different set of emotions [7]. Furthermore, it may also be interesting to explore when the affective expressions may appear to be acted (i.e. part of the role-play). This may shed light on when how the players are actively building the social and affective parts of their experience. Finally, recognizing the players' affective body expressions can also provide information about their action tendency, i.e. their readiness to act upon the events [25].

A problem related to the detection of affective expression is its dependence on the type of action that is performed (e.g. a backhand vs. forehand in a tennis game). Studies on acted body expressions (e.g. [11, 26]) have shown that certain features for affective body expression discrimination appear to be constant over different types of action. However, the fact that these results are based on acted expressions may raise the concern that this could be true only for stereotypical expressions. It would be interesting to explore computational models that can optimize the solution of the affective discrimination problem by automatically exploiting information about

[1] http://www.kaggle.com/c/GestureChallenge. Downloaded on 1 April 2012.

the context (i.e., type of action, identity of the person, etc.). These kinds of approaches have shown promising results (e.g. [27]) in the recognition of emotions by using computational models that co-learn tasks that are orthogonal to emotion recognition (e.g. learning to recognize person identity) by exploiting the knowledge that these tasks are based on quasi-orthogonal (i.e. separate) features. This could be the case with action and emotion. In fact, results by Atkinson et al. [28] have highlighted that, whereas recognition of the type of action being performed (e.g. walking vs. playing tennis) is based on local body joint information, recognition of the affective content of an expression is based on overall measures of body configuration and dynamics.

Conclusions

The emerging full-body technology and the increasingly cheaper motion capture systems offer interesting possibilities for the design and evaluation of entertainment technology. Body movement is a very important source of information about player experience. It offers the means to measure how the player is appropriating the game and at the same time it is a window on the player's affective experience. The field is emerging and providing interesting features for measuring player experience. We propose here to investigate changes in body movement entropy as a way to gain insight on how the player is appropriating the game control. Four different phases were discussed where the profile of such measure may differ: exploration, consolidation, mastering and performing. Furthermore, affective and social body expressions may be used to measure not only how the players feels but also to understand if the players is actively building a hard-fun type of experience or if s/he is looking forward to an easy-fun type instead. When easy-fun is the main motivation of the player, the body patterns to be measured are also (and possibly mainly) the role-play ones rather than only the ones to optimally control the game.

References

1. Muller F., Bianchi-Berthouze, N. (2010) Evaluating Exertion Games Experiences from Investigating Movement Based. *Human-Computer Interaction Series*, Part 4, Springer, 187-207.
2. Niedenthal, P.M., Barsalou, L.W., Winkielman, P., Krauth-Gruber, S., Ric, F. (2005). Embodiment in Attitudes, Social Perception, and Emotion. *Personality and Social Psychology Review* **9**(3), 184–211.
3. Carney, D.R., Cuddy, A.J.C., Yap, A.J. (2010). Power posing: Brief nonverbal displays affect neuroendocrine levels and risk tolerance. *Psychological Science* **21**(10), 1363-1368
4. Petersen, M.G. (2004). Aesthetics of Interaction – A Pragmatist Perspective*. Proceedings Workshop on Aesthetic Approaches to Human-Computer Interaction*, 31- 32.
5. Petersen, M.G., Iversen, O.S., Krogh, P.G. (2004). Aesthetic Interaction – A Pragmatist's Aesthetics of Interactive Systems. *Proceedings on Designing Interactive Systems*
6. Dourish, P. (2001). *Where the Action Is*. MIT Press, Cambridge, MA, USA.
7. Bianchi-Berthouze, N. (in press). Understanding the role of body movement in player engagement. *Human-Computer Interaction,* (in press).

   http://web4.cs.ucl.ac.uk/uclic/people/n.berthouze/BerthouzeHCI12.pdf
8. Isbister, K., Schwekendiek, U., Frye, J. (2011). Wriggle: An Exploration of Emotional and Social Effects of Movement. *Proceeding of SIGCHI conference on Human factors in computing systems*, 1885-1890.
9. Melzer, A., Derks, I., Heydekorn, J., Steffgen, G. (2010). Click or Strike: Realistic versus Standard Game Controls in Violent Video games and Their Effects on Agression, In H.S Yang, R. Malaka, J. Hoshino & J.H. Han (Eds) *Entertainment Computing, LNCS 6243,* Springer: Berlin, 171-182.
10. Isbister, K. and Dimauro, C. (2011). Waggling the form baton: Analyzing body-movement-based design patterns in Nintendo Wii games, toward innovation of new possibilities for social and emotional experience. In *Whole Body Interaction*. D. England, Ed. Springer, London.

11. Kleinsmith, A., and Bianchi-Berthouze, N. (in press). Affective Body Expression Perception and Recognition: A Survey. *IEEE Transaction on Affective Computing*.

12. Pasch, M., Bianchi-Berthouze, N., van Dijk, B., & Nijholt, A. (2009). Movement-based Sports Video Games: Investigating Motivation and Gaming Experience. *Entertainment Computing* **9**(2), 169-180.

13. Nijhar, J., Bianchi-Berthouze, N., Boguslawski, G. (in press). Does Movement Recognition Precision affect the Player Experience in Exertion Games? *International Conference on Intelligent Technologies for interactive entertainment*.

14. Kirsh, D., Maglio, P. (1994). On distinguish epistemic from pragmatic action. *Cog. Sci.* **18**, 513-549.

15. Maglio, P., Wenger, M.J., Copeland, A.M. (2008). Evidence for the role of self-priming in epistemic action: Expertise and the effective use of memory, *Acta Psychologica* **127**(1), 72-88.

16. Shaker, N., Asteriadis, S., Yannakakis, G.N, Karpouzis, K. (2011). A Game-based Corpus for Analysing the Interplay between Game Context and Player Experience. *Affective Computing and Intelligent Interaction Conference; Emotion in Games Workshop*, Springer.

17. Park, J.Y., Yi, J.H. (2006). Gesture recognition based interactive boxing game. *International Journal of Information Technology* **12**(7), 36–44.

18. Park, J.Y. Lee, Y.C., Jo, B.S. Lee, C.W. (2011). Virtual playing ground interface using upper-body gesture recognition. *Workshop on Frontiers of Computer Vision*, pp. 1-5.

19. Reidsma, D., Welbergen, H., van Poppe, R., Bos, P., Nijholt, A.: Towards bi-directional dancing interaction. Harper, R., Rauterberg, M., Combetto, M. (eds.) *ICEC 2006, Lecture Notes in Computer Science*, LNCS 4161, Springer, 1-12.

20. Bleiweiss, A., Eshar, D., Kutliroff, G., Lerner, A., Oshrat, Y., Yanai, Y. (2010). Enhanced interactive gaming by blending full-body tracking and gesture animation. *ACM SIGGRAPH ASIA*.

21. Roccetti, M., Marfia, G., Semeraro, A. (2011). A Fast and Robust Gesture Recognition System for Exhibit Gaming Scenarios. *International Workshop on Distributed Simulation and Online Gaming.*

22. Roccetti, M., Marfia, G., Semeraro, A. (2012). Playing into the Wild: A Gesture-based Interface for Gaming in Public Spaces. *Journal of Visual Communication and Image Representation*, **23**(3), 426-440.

23. Kleinsmith, A., Bianchi-Berthouze, N., & Steed, A. (2011). Automatic Recognition of Non-Acted Affective Postures. *IEEE Transactions on Systems, Man, and Cybernetics, Part B* **41**(4), 1027-1038.

24. Savva, N., Scarinzi, A., & Bianchi-Berthouze, N. (2012). Continuous recognition of player's affective body expression as dynamic quality of aesthetic experience, *IEEE Transactions on Computational Intelligence and AI in Games*.

25. de Gelder, B. (2009). Why bodies? Twelve reasons for including bodily expressions in affective neuroscience. *Philosophical Transactions of the Royal Society* **364**(3), 3475-3484.

26. Roether, C., Omlor, L., Christensen, A., Giese, M.A. (2009). Critical features for the perception of emotion from gait, *Journal of Vision* **8**(6,15), 1-32.

27. Romera Paredes, B., Argyriou, A., Bianchi-Berthouze, N., Pontil, M. (2012). Exploiting Unrelated Tasks in Multi-Task Learning. *Proceedings of International conference on Artificial Intelligence and Statistics*.

28. Atkinson, A.P. (2009). Impaired recognition of emotions from body movements is associated with elevated motion coherence thresholds in autism spectrum disorders. *Neuropsychologia*, **47**(13), 3023-3029

29. D'Mello, S., Graesser, A. (2011). The half-life of cognitive-affective states during complex learning. *Cognition & Emotion* **25**(7), 1299-1308.