Toward a model of computational attention based on expressive behavior: applications to cultural heritage scenarios

D. Glowinski[1], M. Mancas[2], P. Brunet[3], F. Cavallero[1], C. Machy[4], P.J. Maes[5], S. Passchalidou[6], M.K. Rajagopal[7], S. Schibeci[1], L. Vincze[8], G. Volpe[1]

[1] University of Genoa, Italy, [2] University of Mons, Belgium, [3] Queen's University of Belfast, UK, [4] Multitel, Belgium, [5] University of Ghent, Belgium, [6] University of Crete, Greece, [7] Telecom Paris, France, [8] University of Pisa

Abstract

Our project goals consisted in the development of attention-based analysis of human expressive behavior and the implementation of real-time algorithm in EyesWeb XMI in order to improve naturalness of human-computer interaction and context-based monitoring of human behavior. To this aim, perceptual-model that mimic human attentional processes was developed for expressivity analysis and modeled by entropy. Museum scenarios were selected as an ecological test-bed to elaborate three experiments that focus on visitor profiling and visitors flow regulation.

***Index Terms*—museum, computational attention, expressive behavior, complexity.**

I. Human behavior analysis in museum scenarios

The analysis of the behavior exhibited by museum visitors is interesting from different perspectives. In museography, the design of an exhibit or of a visit to an archeological site could greatly benefit from concrete data from the automated tracking and analysis of visitors' behavior, to obtain a profiling of the museographic project. From the perspective of the enhancement of the quality and the intensity of the experience in a museum visit, many directions can be envisaged: from the analysis of the behavior of visitors used to adapt the lighting environments, the communicated museum multimedia content, to the increase of the immersivity and the understanding of cultural content by means of interactive technologies, toward an "active fruition" of cultural content [11]. Furthermore, these issues can provide inspiration toward, for example, possible solutions to the well-known problems of the "Non-Places" which aredefined by Marc Augé as places where no social relationship can take place [2].

Multiple variables affect the museum experience: 1) the artifacts that are exhibited, 2) the visitor's personality, knowledge, motivation or learning style, 3) the presence and dynamics of others around them including friends, family and strangers, and 4) the environmental conditions (e.g., signage, light, temperature). In this sense, museum experience has been described as a *multivariate* one [38]. Other aspects of our daily lives spent in public spaces also show great complexity and sensitivity to multiple social, cultural and psychological influences (e.g., go shopping). However, Bell's *cultural ecologies* ascribe museum visit with three specific qualities: *liminality* (museum are places that embody an experience apart from everyday life, in a differently experienced dimensions of time and space), *engagement* (museums are places where people go to learn, often in an entertaining and exploratory way) and *sociality* (museum should be designed to guide supported activities that increase the interaction between family members, friends and artifacts) [4].

Museums are receiving in the recent years an increasing interest from the Information and Communication Technologies ICT research communities. On one hand, non-invasive systems for monitoring people and user modeling (e.g., ubiquitous computing, ambient intelligence) can enable visitor profiling with reliable quantitative data, which can give new insights on visiting styles. On the other hand, the development of interactive applications can provide visitors with new solutions for active fruition of museum content.

II. Supportive ICT for museums fruition scenarios

A. Profiling visitors

Starting from observations of the behavior of visitors in several museums, the ethnologists Veron and Levasseur [34] argued that visitor behavior can be classified as four "animal-styles": *ant*, *fish*, *butterfly* and *grasshopper*. The *ant* visitor follows a linear path and spends a lot of time observing almost all the exhibits. The *fish* visitor moves mainly in the centre of the room without looking at exhibit's details. The *butterfly* visitor often changes visiting direction and stops frequently. Finally, the *grasshopper* visitor carefully selects a number of exhibits and spends a lot of time observing them while ignoring the others (see Figure 1). This classification have been widely used and supported by quantitative analysis [35, 31, 18, 15, 43]. An alternative simplified museum visitor typology was proposed by Sparacino following Dean [17] that distinguish between three types of visitors: the *busy*, *selective*, and *greedy* visitor type [31]. The *busy* type wants to get an overview of the principal items in the exhibit and see little of everything, the *selective* type wants to see and know in depth only about a few preferred items and the *greedy* type wants to know and see as much as possible without time constraint.

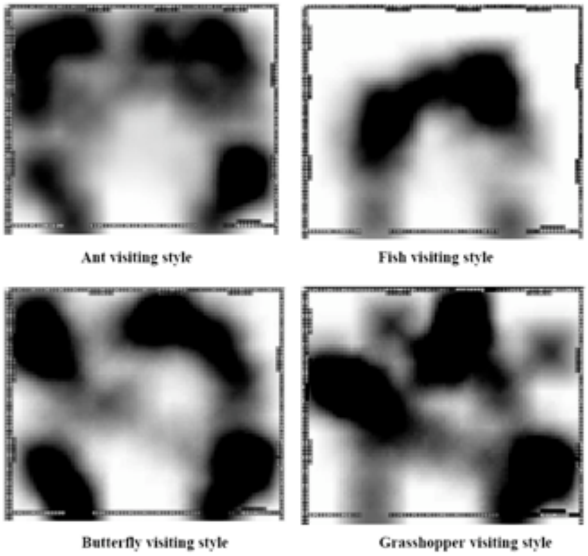


***Fig. 1**: Overview of the four visiting styles developed by Veron and Levasseur* [34] *and modeled with the VU-FLOW system developed by Chittaro et al.* [15]. *The darker areas represent spaces where a visitor spent a lot of time.*

Both visit typologies are based on spatial-temporal patterns that characterize visitor displacements in the museum (e.g., physical path, speed, direction changes, number, location and length of stops). In addition, these patterns of displacement can be employed to identify navigation problems within the museum spaces [15, 30]. Unobtrusive monitoring systems (e.g., ambient intelligence technologies) allows for the automatic capture of physical data related to visitors' behaviors [29]. However, in a number of real-world scenarios, the identification of individuals for the purpose of tracking can be problematic (e.g., occlusion, video coverage of the exhibit) and can require additional manual annotation [30]. More invasive devices (wearable museum [31], virtual environment [15]) have been employed to provide more accurate and robust information about position and orientation, however with the possible drawback of restricting or influencing visitor behavior.

B. Providing visitors with active fruition of museum content

The information automatically collected from movement patterns enable curators to profile visitors and identify design exhibits problems offline. Ambient intelligence and user modeling technologies have also been largely used to extend the possibility of interaction within the museum spaces. A majority of projects have developed context-sensitive handheld prototypes with embedded sensors which are employed to capture visitor current location, in addition to handle more explicit request from visitors.

The Hippie project is a first attempt to develop a context-sensitive adaptive museum guide [28]. Their user model aims to "predict the information needs of a user in a given episode of a visit". The model makes inferences regarding the next exhibit to visit and the next piece of information to present. In the HIPS [26] and the museum wearable project [31], visitor styles, based on the patterns from [34] and [31], serve to assemble appropriate length audio clips for each individual (e.g..for the *butterfly* or *greedy* type, short clips will be displayed). Experimental mobile multimedia systems have also been developed in the MUSE and PEACH projects to personalize information [16, 32]. The PEACH guide provides the visitor with a digital character on their PDA who delivers information on various artifacts within the exhibits. Details about paintings can be accessed through prerecorded video close-ups and a printout can be produced to recapitulate the exhibits the visitor encountered while at the museum. The MUSE project provides virtual access to physically unavailable items according to a visitor's interest.

The e(ch)o project implements hybrid adaptive and adaptable systems to correlate explicit and implicit reactions from users to gain feedback and improve user model [18]. The CHIP project allows a user to generate a personal profile via an online rating system for artwork that is later used by the system to suggest visit itineraries in the museum [1].

In recent years, research has continued on group-based activities. In this perspective, the PDA is thought to provide shared virtual space for coordination and collaboration to help make new connections for museum visitors [4]. The PIL Project, for example, extends results of the PEACH project from the individual to the group level [19, 21]. The authors developed intra-group context-aware communication services that aim at stimulating conversation about the museum contents within the group, during and after the visit. Wakkary observed that the interest for group-based activities vary from research focused on information delivery tours to research focus on game interaction activities [40, 39]. A learning game for school children has been created within the ARCHIE project [33]. It allows visitors to trade museum-specific information to gain points in order to win a game. However, during group-based activities, handheld device like a PDA may distract the visitors from their companion. In this perspective, recent ambient intelligence techniques based on group-centric concepts [36] can reveal fruitful for non-invasive applications in museum environments (Shape project [3], Kurio project [41]). InfoMus – Casa Paganini in particular developed novel user- and group-centric interactive multimedia system architecture enabling an active and social experience of audiovisual content in a playful manner. The first permanent interactive museum exhibitions focused on music performance and full-body movements as first class conveyors of expressive and emotional content. For the Music Atelier of "Città dei Bambini" (Children's City, Genova, 1997), a *sensitive* space was designed to let children exploring music content through expressive body movements.

In the Genovese Maritime museum and the aquarium, systems were implemented for the real-time control and generation of sounds and musical comments related to the content of the museum exhibit ("The Big Blue Boat",2000). Interactive sonification depended on individual presence in specific locations and group movements. Scientific museum served as a testbed for active exploration of scientific experiments to trigger interest and curiosity and to facilitate the commitment of young visitors ("Museo del Balì", Fano, 2004, "Museo Vivo della Scienza - Fondazione IDIS", Napoli). From the perspective of valorization of cultural heritage, recent research conducted in InfoMus Lab - Casa Paganini have provided novel engaging paradigms of interaction with pre-recorded music content, enabling a large number of non-expert users to rediscover the musical heritage (e.g., classical and contemporary music) they may not be familiar with (EU-ICT Project SAME, Sound and Music for Everyone, Everyday, Everywhere, Every Way, www.sameproject.eu). The field of application has been extended to active experience of audiovisual content, in particular in a novel permanent interactive museum exhibition: Palazzi in Mostra, Palazzo Ducale, Genova, Italy, enabling tourists and visitors to explore virtually the UNESCO Treasure of "Palazzi dei Rolli" in Genova (2010).

III. Our Proposal

A. *Analysis of non-verbal expressive gesture*

1) From explicit to implicit tagging

Regarding the user characteristics that need to be modeled, most approaches focus on physical data (movement patterns) to reconstruct visiting style. Higher-level of information related to social or affective interactions can also be retrieved from the analysis of visitors' non-verbal behavior. Vinciarelli labels this process "implicit tagging" [37] in contrast to explicit tagging paradigm in which a data item gets tagged only if a user actually decides to associate tags with it (e.g., adding keywords to the data that are used for indexing and retrieval purposes). Discrete emotions of visitors (e.g. anger) or attitudinal states (e.g. boredom) can be communicated through full-body or body-part movements such as the hands and head. As mentioned by Nass and Brave, emotions are displayed in a similar way in human-human and in human-computer interactions [8]. These categories of gesture that convey an affective message are called expressive gestures [, camurri2005cea].

According to Kurtenbach and Hulteen, a gesture can be defined as "a movement of the body that contains information" [22]. Thus, gestures can be named expressive since the information they carry includes content related to the emotional sphere. Expressive gesture, as a key aspect of human behavior and in particular of expressive human behavior, became particularly relevant in recent years (e.g., see the post-proceedings of Gesture Workshops 2003, 2005, and 2007). Psychological studies have been a rich source for research on automatic analysis of expressive gesture since they identified which features are most significant [27, 42, 7]. A further relevant source has been research in the humanistic tradition, in particular choreography. As a major example, in his Theory of Effort, choreographer Rudolf Laban [23] describes the most significant qualities of movement. Starting from these sources, several systems for analysis of expressive gesture were developed [10, 20, 5]. Our approach starts from the multilayered framework for automatic expressive gesture analysis proposed by Camurri et al. [12]. In this framework, expressive gestures are described with a set of motion features that specify how the expressive content is encoded. The EyesWeb XMI platform for synchronized analysis of multimodal datastreams (www.eyesweb.org) allows for the extraction of a wide collection of motion features from video and sensors data streams.

2) From static to dynamic modeling

Recently, we developed a novel technique to make analysis of expressive gesture context-sensitive and adaptive. Our approach draws upon information theory and computational attention and has resulted in a salient index that detects salient (i.e. unusual) behaviors. Behavior saliency accounts for the distance, in a selected time window, between the expressive features measured on an individual and the averaged values measured on all the components of the group. Saliency can be computed with respect to time or to space depending on the behavioral features that are considered (e.g., dynamics for time, trajectory for space).

Behavior saliency can be modeled starting from recent results obtained in the field of *computational attention*. The aim of computational attention is to automatically predict human attention based on different kinds of data such as sounds, images, video sequences, smell, or taste. In this framework, salient behavior is understood as a behavior capturing the attention of the observer. Whereas many models were provided for attention on still images, time-evolving two-dimensional signals such as videos have been much less investigated. Nevertheless, some of the authors providing static attention approaches generalized their models to the time dimension (for a detailed review, see [24]). Motion has a predominant role and the temporal contrast of its features is mainly used to highlight important movements. Boiman and Irani [6] provided an outstanding model which is able to compare the current movements with others from the video history or video database. Attention is related to motion similarity. The major problem of this approach is in its high computational cost. In order to get an efficient model of motion attention and behavior salience, we developed a three-level saliency-based model [24]. At the first level, motion features are compared in the spatial context of the current video frame; at the intermediate level, salient behavior is analyzed on a short temporal context; at the third level, computation of saliency is extended to longer time windows. An attention/saliency index is computed at each of the three levels based on an information theory approach. Analysis of salient behavior was recently extended to measures of complexity namely *Multi-scale Entropy* (MSE). This method aims at evaluating the complexity of finite length time series. It is based on the analysis of the entropy values assigned to the original time series and to coarse-grained time series, each of which represents the system's dynamics on a different scale.

B. Pilot experiments

At the occasion of the Enterface09 summer school, three pilot experiments were carried on to address issues related to visitor profiling and visitor-flow regulation.

1) Visitor profiling

A first setup was created to implement and test a real-time dynamic modeling of Veron and Levasseur visiting styles [34] based on the long-term saliency index. Five Arcimboldo's painting reproductions were displayed in a gallery style on the stage of the Casa Paganini auditorium. The typical spatial configuration theorized by Levasseur and modeled in many recent studies (see *section II. A*) was followed: three paintings on the length side and one on each of the width sides of the stage (see Figure 2).

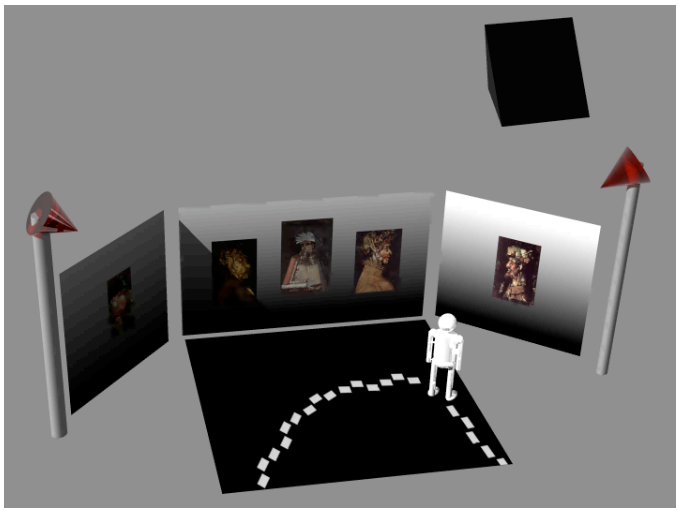


Figure 2. *The gallery style setup : illustration of a visitor in the five paintings museum room*

Participants were instructed to view the images as they typically would in a museum. Each participant was asked to visit the gallery set up three time: (i) alone, (ii) in presence of two confederates that view paintings from empty spaces (*empty* condition) and (iii) in presence of two confederates that view paintings by standing directly in front of them (*full* condition). These single user and multi-user scenarios were created respectively to (i) observe and model visiting styles and (ii) to put in evidence how the presence of others influence visiting style. Five paintings from the Arcimboldo opera pre-rated to be similar in attractiveness were selected for the gallery. We thus avoid that visual characteristics of a particular painting could differentially capture the visitor's attention.

Participants' movements were observed from a single infra-red video cam positioned 12 meters above. Motion history images (MHI) were used to compute the position, the direction and the velocity of participants over long-time scales (e.g., 4 minutes). The saliency index computed from these features allowed to build a model of the scene highlighting the regions where salient behaviors, characterizing visiting styles, could be observed [25]. The unusual direction changes that characterize the *butterfly* style or the long periods of observating select paintings typical of the *grasshopper,* for example, could all bedetected. Four learnt models were successfully built that respectively integrate the characteristics of each Levasseur animal-styles. Tests on 10 male participants revealed that the main styles of the visitor could be dynamically modeled in single and multi-users scenarios. Results revealed that most participants followed the ant-like style when alone and a grasshopper-like style in presence of others. Contrary to other static classifications [26, 31, 43], our model could inform in real-time on how the current visit deviate from a pre-determined pattern [see Figure 3]. Less typical behaviors could actually be retrieved that combine more animal-like styles. Further tests will be needed that could lead to more detailed typologies of visiting styles.

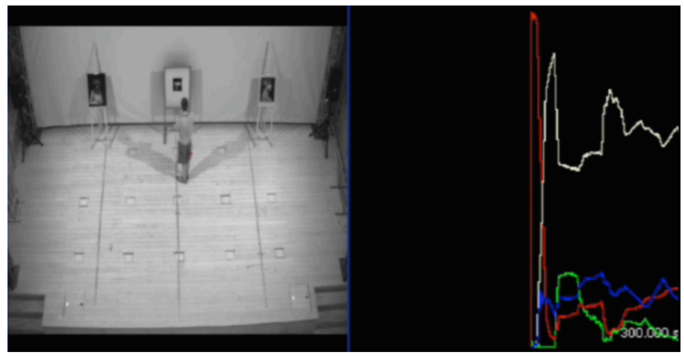


Figure 3. *snapshot of an individual visit and real-time visualization of each visiting style value (ant-green, grasshopper-blue, butterfly-red, fish-white)*

Personality questionnaires were also administered to the participants to investigate any possible correlations between visiting styles and behaviors observed in the various scenarios with personality traits. Participants completed the short form version of the Big Five Inventory (BFI) and the 5-highest loaded shyness items and the 5-highest loaded sociability items [9] from the Cheek and Buss Shyness and Sociability Scale [13, 14]. Results suggest that participant's visiting style can be differentially affected by the presence of others according to his sociability score. Two classes of people were highlighted: those who change their style when other visitors are present (on the path they would normally take) and those who do not. In the full condition, we found that the five participants that deviated from the ant pattern scored statistically significantly lower on the sociability scale than the five participants that maintained their ant pattern [$F(1,7) = 8.556$, $p = .022$)]. In our sample, people who feel the least comfortable with others tend to drastically change their visiting style to avoid standing too close other people.

2) Regulating visitor-flow

The second and third experiments were setup to explore interactive applications that could regulate visitors flow in a museum. The experiments again took place on the Casa Paganini stage with the same video setup for tracking participants' displacements.

The second experiment aimed, in particular, at finding visual cues that would guide a visitor to a target position. In our test-case, the size and the resolution of the visual display (an image of an Italian historical Palace) were mapped with the distance of the visitor's current position from the target position (see figure 4). When the participant approached the target position, the image projected on the 8*4 meters screen that stood back along the stage, appeared in its full resolution and size. When the participants moved away, the image decreased and blurred.

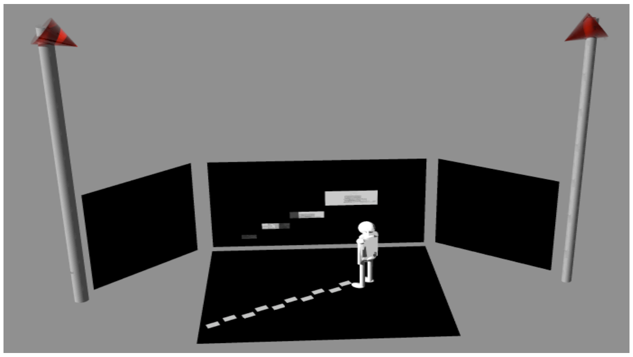


Figure 4*. The visitor located in the target position is able to watch the projection in full size and full resolution (no blur effect).*

Various mapping combination were explored (e.g., trials including only blur effect without size changes of the images, trials including only participant displacement along horizontal axis). As illustrated in Figure 5, tests on 14 participants revealed that the target position was reached more directly and rapidly (less than one minute) when the size and resolution of the image were both mapped to the participant displacement on the horizontal and depth axes of the stage. A set of expressive features was developed to analyze participants' space occupation during the experiment and evaluate the interaction design thoroughly.

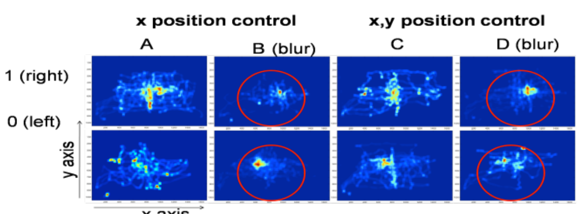


Figure 5*. Expressive features related to space occupation. Example of the max Density features, visualization of 14 users mean positions over time.*

Psychological profiles were also submitted to the participants. People who performed low on the sociability scale (i.e. introvert people) reported greater interest in the size/resolution manipulations ($r = -.606$, $p = .022$).
The third experiment aimed at regulating visitor-flow in a museum room by guiding each individual to available artworks. The gallery style setup described in the first experiment was reproduced. A long-term motion attention model of the scene was developed to compute how the region surrounding each painting was visited as compared to the others. Salient regions were then sorted out according to their density level. Visitor-flow was regulated by attracting a new visitor's attention by means of a projected arrow to the most salient regions, i.e, the region surrounding artwork that was currently not being viewed by anyone else (see Figure 6).

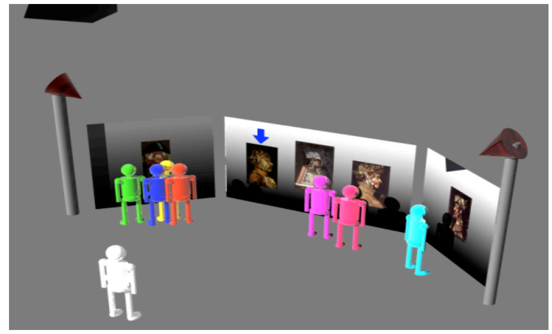


Figure 6*. A view of the interaction: new visitors entering in the room were encouraged to watch the less visited paintings*

IV. Conclusion and Future Work

The work presented was achieved during the one-month enterface09 summer school, and it should be considered as a starting point for future analysis work, currently in progress. In particular, we investigated the potential applications of computational attention models to museum scenarios. Three pilot experiments were conducted to address issues related to visitor profiling and visitors flow regulation. Preliminary results revealed that the standard Veron and Levasseur four visiting styles could be modeled dynamically using a real-time long-term attention model. Visitors expressive behavior in the museum-like exhibit was further considered by analyzing space occupation during the experiments and exploring possible correlations with personality traits. Basing on previous results, an interactive application aimed at supporting natural expressive behavior was designed and tested to regulate visitor-flow. A last consideration is on the first successful use of the Casa Paganini site as a test-bed for developing active fruition paradigm for museum applications.

Acknowledgments

This work has been achieved in the framework of the eNTERFACE 2009 Workshop at the Casa Paganini – InfoMus Lab of the University of Genova (Italy). It was also included in the Numédiart excellence center (www.numediart.org) project 3.1 funded by the Walloon Region, Belgium. Finally, this work has been partially supported by the Walloon Region with projects BIRADAR, ECLIPSE, and DREAMS, and by EU-IST Project SAME (Sound And Music for Everyone Everyday Everywhere Every way). We also thank Prof. Bracco, Chiorri, Schenone for their precious advice.

References

[1] L. Aroyo, N. Stash, Y. Wang, P. Gorgels, and L. Rutledge. Chip demonstrator: Semantics-driven recommendations and museum tour generation. *Lecture Notes in Computer Science*, 4825:879, 2007.

[2] M. Augé and J. Howe. *Non-places: Introduction to an Anthropology of Supermodernity*. Verso Books, 1995.

[3] Liam Bannon, Steve Benford, John Bowers, and Christian Heath. Hybrid design creates innovative museum experiences. *Commun. ACM*, 48(3):62–65, 2005.

[4] G. Bell. Making Sense of Museum: The Museum as' Cultural Ecology': A study. Technical report, 2002.

[5] D. Bernhardt and P. Robinson. Detecting Affect from Non-stylised Body Motions. *Lecture Notes in Computer Science*, 4738:59, 2007.

[6] O. Boiman and M. Irani. Detecting Irregularities in Images and in Video. *International Journal of Computer Vision*, 74(1):17–31, 2007.

[7] R.T. Boone and J.G. Cunningham. Children's Decoding of Emotion in Expressive Body Movement: The Development of Cue Attunement. *Developmental Psychology*, 34:1007–1016, 1998.

[8] S. Brave and C. Nass. Emotion in human-computer interaction. *The Human-Computer Interaction Handbook: Fundamentals, Evolving Technologies and Emerging Applications*, pages 81–96, 2002.

[9] M.A. Bruch, J.M. Gorsky, T.M. Collins, and P.A. Berger. Shyness and sociability reexamined: A multicomponent analysis. *Journal of Personality and Social Psychology*, 57(5):904–915, 1989.

[10] A. Camurri, B. Mazzarino, and G. Volpe. Analysis of Expressive Gesture: The Eyes Web Expressive Gesture Processing Library. *Lecture notes in computer science*, pages 460–467, 2004.

[11] A. Camurri and G. Volpe. Active and personalized experience of sound and music content. In *Proc. IEEE International Symposium on Consumer Electronics ISCE 2008*, pages 1–4, 14–16 April 2008.

[12] A. Camurri, G. Volpe, G. De Poli, and M. Leman. Communicating Expressiveness and Affect in Multimodal Interactive Systems. *IEEE Multimedia*, pages 43–53, 2005.

[13] JM Cheek. The revised Cheek and Buss shyness scale. *Unpublished manuscript, Wellesley College*, 1983.

[14] J.M. Cheek and A.H. Buss. Shyness and sociability. *Journal of Personality and Social Psychology*, 41(2):330–339, 1981.

[15] L. Chittaro, R. Ranon, and L. Ieronutti. VU-Flow: a visualization tool for analyzing navigation in virtual environments. *IEEE Transactions on Visualization and Computer Graphics*, pages 1475–1485, 2006.

[16] J. Davis. *The MUSE Book (Museums Uniting with Schools in Education: Building on our Knowledge)*. 1996.

[17] D. Dean. *Museum exhibition: theory and practice*. Routledge, 1996.

[18] M. Hatala and R. Wakkary. Ontology-based user modeling in an augmented audio reality system for museums. *User Modeling and User-Adapted Interaction*, 15(3):339–380, 2005.

[19] S. Jbara, T. Kuflik, P. Soffer, and O. Stock. Context Aware Communication Services in" Active Museums. In *IEEE International Conference on Software-Science, Technology & Engineering, 2007. SwSTE 2007*, pages 127–135, 2007.

[20] A. Kapur, A. Kapur, N. Virji-Babul, G. Tzanetakis, and P.F. Driessen. Gesture-Based Affective Computing on Motion Capture Data. *Lecture Notes in Computer Science*, 3784:1, 2005.

[21] T. Kuflik, J. Sheidin, S. Jbara, D. Goren-Bar, P. Soffer, O. Stock, and M. Zancanaro. Supporting small groups in the museum by context-aware communication services. In *Proceedings of the 12th international conference on Intelligent user interfaces*, pages 305–308. ACM New York, NY, USA, 2007.

[22] G. Kurtenbach and E.A. Hulteen. Gestures in Human-Computer Communication. *The Art of Human-Computer Interface Design*, pages 309–317, 1992.

[23] R. Laban and FC Lawrence. *Effort*. Macdonald and Evans, 1947.

[24] M. Mancas. Relative influence of bottom-up and top-down attention. *Attention in Cognitive Systems, Lecture Notes in Computer Science*, Volume 5395/2009:pp. 212–226, February 2009.

[25] M. Mancas, D. Glowinski, P. Bretéché, J. Demeyer, T. Ravet, G. Volpe, and A. Camurri. Gestures Saliency: a Context-based Analysis. In *Proceedings of the Gesture Workshop*, 2009.

[26] P. Marti. Design for art and leisure. *Proceedings of ICHIM 2001*, pages 387–397, 2001.

[27] M. Meijer. The contribution of general features of body movement to the attribution of emotions. *Journal of Nonverbal Behavior*, 13(4):247–268, 1989.

[28] R. Oppermann and M. Specht. A context-sensitive nomadic exhibition guide. *Lecture notes in computer science*, pages 127–142, 2000.

[29] N. Shadbolt. Ambient Intelligence. *IEEE Intelligent Systems*, 18:2–3, 2003.

[30] D. Shell, S. Viswanathan, J. Huang, R. Ghosh, J. Huang, M. Mataric, K. Lerman, and R. Sekuler. Spatial Behavior of Individuals and Groups: Preliminary Findings from a Museum Scenario.

[31] F. Sparacino. The Museum Wearable: real-time sensor-driven understanding of visitors' interests for personalized visually-augmented museum experiences. pages 17–20, 2002.

[32] O. Stock, M. Zancanaro, P. Busetta, C. Callaway, A. Kr\"uger, M. Kruppa, T. Kuflik, E. Not, and C. Rocchi. Adaptive, intelligent presentation of information for the museum visitor in PEACH. *User Modeling and User-Adapted Interaction*, 17(3):257–304, 2007.

[33] H. Van Loon, K. Gabri\"els, K. Luyten, D. Teunkens, K. Robert, K. Coninx, and E. Manshoven. Supporting social interaction: A collaborative trading game on pda. *Selected papers from Museums and the Web*, 2007:41–50, 2007.

[34] E. Veron and M. Levasseur. *Ethnographie de l'exposition*. Centre Georges Pompidou, 1983.

[35] E. Veron, M. Levasseur, and J.F. Barbier-Bouvet. Ethnographie de l'exposition: l'espace, le corps et le sens. 1989.

[36] A. Vinciarelli, M. Pantic, and H. Bourlard. Social signal processing: state-of-the-art and future perspectives of an emerging domain. 2008.

[37] A. Vinciarelli, N. Suditu, and M. Pantic. Implicit human-centered tagging. In *Proc. IEEE International Conference on Multimedia and Expo ICME 2009*, pages 1428–1431, June 28 2009–July 3 2009.

[38] D. Vom Lehn, C. Heath, and J. Hindmarsh. *Exhibiting interaction: Conduct and collaboration in museums and galleries*, volume 24. Univ California Press, 2001.

[39] R. Wakkary, M. Hatala, Y. Jiang, M. Droumeva, and M. Hosseini. Making sense of group interaction in an ambient intelligent environment for physical play. pages 179–186, 2008.

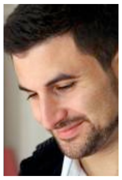
[40] R. Wakkary, K. Muise, K. Tanenbaum, M. Hatala, and L. Kornfeld. Situating Approaches to Interactive Museum Guides. *Museum Management and Curatorship*, 23(4):367–383, 2008.

[41] Ron Wakkary, Marek Hatala, Kevin Muise, Karen Tanenbaum, Greg Corness, Bardia Mohabbati, and Jim Budd. Kurio: a museum guide for families. In *TEI '09: Proceedings of the 3rd International Conference on Tangible and Embedded Interaction*, pages 215–222, New York, NY, USA, 2009. ACM.

[42] H.G. Wallbott. Bodily expression of emotion. *Eur. J. Soc. Psychol*, 28:879–896, 1998.

[43] M. Zancanaro, T. Kuflik, Z. Boger, D. Goren-Bar, and D. Goldwasser. Analyzing Museum Visitors' Behavior Patterns. *Lecture Notes in Computer Science*, 4511:238, 2007.

Donald Glowinski.



Donald Glowinski, Paris, 27-02-1977. His background covers scientific and humanistic academic studies as well as high-level musical training.- EHESS (Ecole des Hautes Etudes en Sciences Sociales) MSc, in Cognitive Science, CNSMDP (Conservatoire National Supérieur de Musique et de Danse de Paris) MSc in Music and Acoustics, Sorbonne-Paris IV MSc. in Philosophy. He recently obtained a Phd in computing engineering at InfoMus Lab – Casa Paganini, in Genoa, Italy. (dir: Prof. Antonio Camurri).

He was chairman of the Club NIME 2008 (New Interfaces for Musical Expression), Genoa, 2008. His research interests include multimodal and affective human-machine interactions. He works in particular on the modeling of automatic gesture-based recognition of emotions.

Matei Mancas.

Matei Mancas was born in Bucarest in 1978. He holds an ESIGETEL (Ecole Supérieure d'Ingénieurs en informatique et TELecommunications, France) Audiovisual Systems and Networks engineering degree, and a Orsay University (France) MSc. degree in Information Processing. He also holds a PhD in applied sciences from the FPMs (Engineering Faculty of Mons, Belgium) on computational attention since 2007.

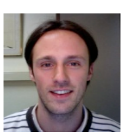
His past research interest is in signal and, in particular, image processing. After a study on nonstationary shock signals in industrial tests at MBDA (EADS group), he worked on medical image segmentation. He is now a Senior Researcher within the Information Processing research center of the Engineering Faculty of Mons, Belgium. His major research field concerns computational attention and its applications.

Paul M. Brunet

Paul M. Brunet was born on February 12, 1980 in Sudbury, Canada. In September, 2009, he obtained a PhD in Developmental Psychology from McMaster University in Hamilton, Canada. Previously, he held a one-year fixed-term Assistant Professor position at Mount Saint Vincent University in Halifax, Canada. Currently, he is a Research Fellow under the direction of Prof. Roddy Cowie at Queen's University Belfast in Belfast, Northern Ireland. Paul is also a member of the Social Signal Processing Network.

His research interests include the effects of context and individual differences on social communicative behavior, the social signals of politeness, the influence of individual differences in personality (in particular shyness and sociability) in typical development, and cyberpsychology.

Pieter-Jan Maes



Pieter-Jan Maes was born on May 16, 1983 in Kortrijk, Belgium. He is currently working on a PhD project supervised by Prof. Dr. Marc Leman, director of the Department of Musicology (IPEM) at Ghent University.

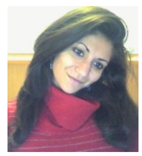
His research interests are grounded in the embodied music cognition paradigm and cover the relationship between movement, sound and musical meaning. Based on results of experimental research, he develops music HCI-applications for the music education, performance and gaming sector.

Francesca Cavallero.

Francesca Cavallero, Genova, 27-12-1982. Coming from humanistic academic studies (she holds the Master's degree in Arts and Multimedia at University of Genova, DAMS - Discipline delle Arti, della Musica e dello Spettacolo, with a thesis on evaluation issues on new paradigm of embodied active listening: a specific case study has been developed on the evaluation of the behavior of subjects using an interactive installation), she is PhD student in Arts and New Technologies (DIRAS - Liberal-Arts Faculty, University of Genova).

From 2006 she collaborates with Casa Paganini InfoMus Lab (dir: Proff. Antonio Camurri). Her research interests concern the user behavior in museographic contexts, to develop new models of active fruition for cultural assets.

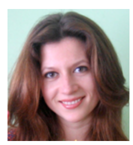
Stefania Schibeci



Stefania Schibeci, Sanremo, 02-04-1982. Her training is in humanistic academic studies; she holds the Master's degree in Arts and Multimedia at University of Genova, DAMS - Discipline delle Arti, della Musica e dello Spettacolo, with a thesis about the importance of the body concept in the art of XX s (in particular in the Pina Bausch Tanztheater, in Pippo Delbono's and Societas Raffaello Sanzio's theatre and in the body art).

He was chairman of the Club NIME 2008 (New Interfaces for Musical Expression), Genoa, 2008. His research interests include multimodal and affective human-machine interactions. He works in particular on the modeling of automatic gesture-based recognition of emotions.

Laura Vincze.



Laura Vincze was born on April 8^{th}, 1982 in Cluj-Napoca, Romania. She is a PhD student in Linguistics, University of Pisa. Her research interests include multimodal communication, persuasion (non verbal and verbal strategies) in political discourse. She recently concluded a research period at the Faculty of Humanities, University of Amsterdam where she focused on the pragma-dialectical approach to argumentation.

In 2008 Laura held a seminar at the University of RomaTre on analysis of non verbal signals of agreement/disagreement and dominance/submission in political debates.

Manoj .K. Rajagopal

Manoj kumar Rajagopal was born on February 9 , 1982 in Mettur Dam , India. He is currently working on PhD project supervised by Dr.Patrick Horain ,Telecom ,Sudparis ,France and Dr.Catherine Pelachaud , Telecom Paristech , France.

His research interest are Machine Learning , Communicative gestures and Human Computer interaction. Presently he is working on style parameters for the human communicative gestures also to develop an avatar for the gestures communication of different style using GRETA.

Stella Passchalidou

Stella Paschalidou was born in Thessaloniki in 1977. She holds a BSc in Physics (Aristotle Univ. Thessaloniki) and an MSc in Music Technology (Univ. of York). She has been working since 2004 as a teaching assistant at the TEI of Crete, dept. of Music Technology&Acoustics and has worked in the Telecommunications private sector in the past.

Her main interests include multimodal interactive systems for musical applications and real-time analysis of expressive content, especially in orally transmitted music traditions

Gualtiero Volpe.

Gualtiero Volpe, Genova, 24-03-1974, PhD, computer engineer. He is assistant professor at University of Genova. His research interests include intelligent and affective human-machine interaction, modeling and real-time analysis and synthesis of expressive content in music and dance, multimodal interactive systems.

He was Chairman of V Intl Gesture Workshop and Guest Editor of a special issue of Journal of New Music Research on "Expressive Gesture in Performing Arts and New Media" in 2005. He was co-chair of NIME 2008 (New Interfaces for Musical Expression), Genova, 2008. Dr. Volpe is member of the Board of Directors of AIMI (Italian Association for Musical Informatics).