# Behaviour Monitoring and Interpretation
## A Computational Approach to Ethology

Björn Gottfried

TZI, University of Bremen

**Abstract.** Behaviour Monitoring and Interpretation is a new field that developed gradually and inconspicuously over the last decades. With technological advances made at the sensory level and the introduction of ubiquitous computing technologies in the nineties this field has been pushed to a new level. A common methodology of many different research projects and applications can be identified. This methodology is outlined as a framework in this paper and supported by recent work. As a result it shows how BMI automates ethology. Moreover, by bringing in sophisticated AI techniques, it shows how BMI replaces a simple behaviour-interpretation mapping through computational levels between observed behaviours and their interpretations. This is similar to the way of how functionalism and cognitive sciences enabled new explanation models and provided an alternative approach to behaviourism in the early days of AI. First research results can be finally given which back up the usefulness of BMI.

## 1 Introduction

This paper gives an introduction to the field of Behaviour Monitoring and Interpretation, BMI for short. BMI picks up problems investigated by ethologists: On the one hand, ethology is a branch of knowledge dealing with human character, with its formation and evolution. On the other hand, ethology is the scientific and objective study of animal behaviour especially under natural conditions [22]. BMI opens up a new trend in ethology, namely that ethological problems are tackled by means of a computational methodology. This opens up new chances and opportunities.

It is the ultimate goal of BMI to make intentions, desires, and goals explicit; more generally, every kind of information which is implicit in observable phenomena, in particular behaviours of man and beast. While this has been the realm of ethologists before computers entered the scene, technological advances approach problems in this field with electronic devices which get ever more accurate and precise, and even allow the acquired data to be evaluated with a great body of methods developed in computer science, especially Artificial Intelligence. The annual BMI workshop is a forum for discussing advances in this field [9,10].

Section 2 gives an overview of a number of applications which pertain to the BMI field, showing what BMI is about. At the same time, a framework is outlined according to which BMI applications usually adhere. On this basis, in Section 3, we are able to argue why it makes sense to introduce the notion of BMI. Conclusions drawn from these considerations are eventually provided in Section 4.

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## 2 The BMI Framework

A number of BMI applications are provided as an introduction to this field. A common framework and typical AI methods employed in this area are identified.

### 2.1 Example Scenarios

Two initial examples illustrate the objective of BMI. Behaviour patterns of mice living in a semi-natural environment are investigated by [18]. They compare motion behaviours of mice who have a genetic predisposition to develop Alzheimer's disease with their wild-type conspecifics. Aim of this project is the systematic support of behavioural observations by humans. For this purpose an RFID system is installed in the cage where the mice live in order to capture their positions. The cage comprises a number of different levels; at the highest level a video monitoring system is installed capturing more precisely the motion behaviours. The left part of Fig. 1 shows how this research project partitions into different abstraction layers with the bottom layer representing the behaviours of interest. By contrast, the top layer shows the interpretation of the observed behaviours. All intermediate layers mediate between observation and interpretation.

Another example, which at first sight looks somewhat different, fits into this very same schema. In [24] motion patterns of pedestrians going shopping are investigated. First, people are observed without knowing anything about it; for this purpose a hand-tracking tablet computer with a digital map is used in order to record the paths of the pedestrians in this map. Second, the people who have been observed get interviewed in order to let them tell a little bit about themselves, their intentions and social background. Finally, they get further tracked, this time equipped with a Bluetooth Smartphone or a GPS logger for indoor and outdoor tracking, respectively. The acquired data is analysed by clustering the obtained trajectories and by using speed histograms. As a result there are

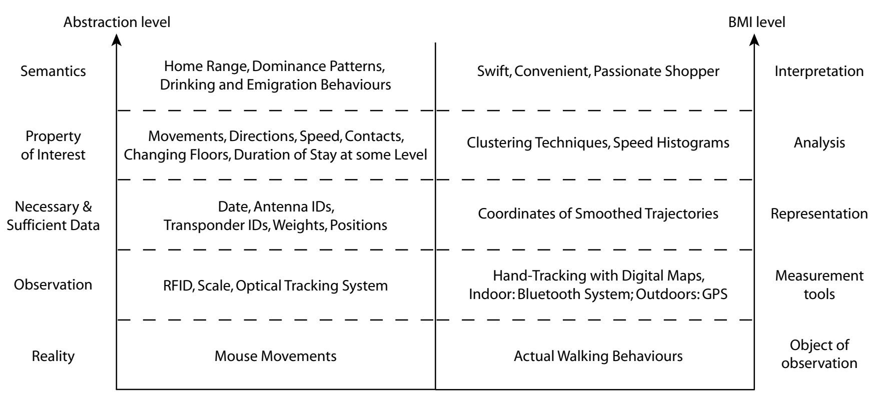


**Fig. 1.** Abstraction layers of two BMI scenarios

basically three types of shoppers identified, namely swift, convenient, and passionate shoppers. The right part of Fig. 1 summarises this study.

Both studies show the usual sequence of abstraction layers which can be found in each typical BMI application. The bottom layer represents the reality, and thus, the object of interest, in our examples, movements of mice and pedestrians. The second layer is about the observation of the object of interest, here by means of such techniques as RFID, Bluetooth, or GPS. The acquired data is frequently preprocessed (e.g. smoothing, detection of outlier) and data representations are chosen for storing the data in an appropriate structure, at the third layer; here, for trajectory positions and other positional information, such as RFID antennas as path landmarks. The fourth layer is about analysing the data, for example in order to determine the duration of staying at some level in the cage or to cluster similar trajectories of different pedestrians. Eventually, the top layer represents the result one is looking for, that is the home range of a mouse or its drinking behaviour or to tell apart swift shoppers from those who enjoy going shopping.

The conventional approach in ethology looks for a (direct) mapping between the bottom layer and the top layer. BMI is distinguished by automating this mapping. Additionally, as opposed to the research direction of behaviourism, BMI enables an arbitrary complex functionality mediating between observation and interpretation. For this purpose a multitude of AI techniques is employed, as we shall learn in the following.

### 2.2 The Employment of AI Techniques in BMI

From the point of view of AI the upper layers are of most interest. While the bottom layer just represents the object of interest, the second layer from below is about measurement tools. Smart Floors show that even this sensory level gets ever more intelligent [34]. The three top layers are basically about knowledge representation: while the third layer focuses on representational issues, the fourth layer is mainly about reasoning, and the top layer again about representations. The distinction between the third and fifth layers is that the former starts with representing the raw sensory data while the top layer seeks for an appropriate representation of the semantics of the observed phenomena. In the following we shall look at a couple of BMI investigations. We learn that in fact a broad spectrum of AI techniques is employed.

Since many BMI questions concern the spatial and temporal behaviours of people, corresponding representations are discussed by several authors [31,19,11,39]: [31] model concepts of human motion such as *go towards*, *approach* and *stop*, [19] model topological and [39] ordinal motion behaviours. These approaches are about the representation of movements. By contrast [17] consider their interpretation. Employing formal grammars they map observed behaviours to intentions in such a way that crossing dependencies of behaviours which do not directly follow each other can be represented. Similarly, temporal sequences of hand postures are analysed by formal grammars in order to recognise hand gestures [8].

Daily life behaviours of people are analysed by means of learning techniques to discover typical actions [5]; they look for repeating patterns of dependencies among sensor events. Learning techniques are also deployed by [12] for detecting high-level activities, such as morning care activitis like brushing one's teeth; they employ an unsupervised k-means clustering approach in combination with Hidden Markov Models for mapping cluster membership onto more abstract activities. As opposed to the previously discussed movement representations, those learning systems do also look at sensor events which are triggered when, for instance, a cabinet door is opened. In other words, BMI does not solely take into account the behaviours of people as they are directly observable, but also behaviours which are indirectly observable by means of changes in the environment.

A sophisticated behaviour recognition system based on video technology is investigated by [36]. Applied to dynamic indoor scenes and static building scenes, they implement a number of submodules: objects must be recognised, classified and tracked, qualitative spatial and temporal properties must be determined, behaviours of individual objects must be identified, and composite behaviours must be determined to obtain an interpretation of the scene as a whole. They describe how these tasks can be distributed over three processing stages (low-level analysis, middle layer mediation and high-level interpretation) to obtain flexible and efficient bottom-up and top-down processing in behaviour interpretation. [36] further point out that behaviour recognition appears to be a restricted topic with a focus on several different behaviour recognition tasks. They mention the following typical applications: vandalism in subway stations [40], thefts at a telephone booth [14], the filling up at a gas station [27], the identification of activities at the airport [37] or the placing of dishes on a table [15].

Particular complex monitoring systems are developed in the field of distributed smart cameras. In [1] the authors propose a vision-based framework to provide quantitative information of the user's posture. While quantitative knowledge from the vision network can either complement or provide specific qualitative distinctions for AI-based problems, these qualitative representations can offer clues to direct the vision network to adjust its processing operation according to the interpretation state. In this way they show by example that the proposed BMI framework is not a one-way street. One of their application examples is fall detection.

A well appreciated area for analysing typical BMI problems is soccer, the RoboCup community being indeed largely faced with analysing behaviours. In their paper [41] present a qualitative, formal, abductive approach, based on a uniform representation of soccer tactics that allows to recognise and explain the tactical and strategic behaviour of opponent teams based on past observations. A framework for argumentation and decision support in dynamic environments is investigated by [33]. This framework defines arguments which refer to conceptual descriptions of the given state of affairs. Based on their meaning and based on preferences that adopt specific viewpoints, it is possible to determine consistent positions depending on these viewpoints, allowing the interpretation of spatiotemporal behaviours.

While AI techniques frequently aim at automating the whole process, there are approaches which more rely on the skills of human beings. One such field is the area of *visual analytics* that combines automatic techniques to data analysis with humans skills, mainly vision and reasoning, and in this way relates to diagrammatic reasoning. The problem which is addressed in the context of visual analytics concerns mainly massive collections of data (as they are obtained throughout BMI applications) and the problem that it is hardly possible to do without human abilities to identify interesting patterns in the data. [3] consider the case of large amounts of movement data. In their scenario vehicles are equipped with GPS and they analyse typical paths and look for points of interest which can be derived purely from the observations.

While most approaches mentioned so far concentrate on the monitoring of the behaviours of individuals, we should also mention group behaviours, as of interest in the case of disaster management. While [44] provide a general classification scheme for behaviours of collectives, [13] investigate techniques to space-use analysis on a university campus. Regarding AI, interactions within groups, and in particular their simulation, is the realm of Multiagent Systems [38].

## 3 The Role of BMI in Related Areas

There are a lot of directions in AI and a multitude of areas where AI techniques play an essential role. The question arises whether it is necessary to talk about yet another area, as we do with BMI. In the following we will provide a couple of arguments for the integrating role of BMI.

First and foremost ubiquitous computing technologies have been devised in the last decade [42]. There is a fast development in this area which is mainly due to advances made with accurate and cheap sensor technologies. That is, with these technologies a fundamental basis for BMI applications has been established. Additionally the notion of ubiquitous computing closely relates to pervasive computing. The latter followed the former, is mainly coined by industry, and puts more emphasis on networks while ubiquitous computing is more human-centred. Both directions provide essential means for the BMI field.

Applications, as we have seen in the previous section, can be found in very different areas. One such area is the field of Ambient Intelligence (AmI) [6]:

> *The basic idea behind AmI is that by enriching an environment with technology (sensors, processors, actuators, information terminals, and other devices interconnected through a network), a system can be built such that based on the real-time information gathered and the historical data accumulated, decisions can be taken to benefit the users of that environment* [4].

BMI should be regarded as a subfield of AmI that deals with the *(real-time) information gathering* part and the evaluation of the gathered information. While AmI is a growing field that gets ever more complex it becomes useful to identify subfields, like BMI, that avoid losing track of things.

But there are other areas than AmI which can be found in different disciplines. For example, there is a broad community of geographers who are interested in investigating spatiotemporal phenomena of moving objects, e.g. in the context of wayfinding tasks [30,43]; and from the computational point of view [28,25,26]. Taking their work, it shows that there is a clear intersection with the AI community that investigates qualitative spatiotemporal phenomena [7]. BMI covers this area of intersection by focusing on the methodologies for investigating spatiotemporal behaviours.

Having motivated the notion of computational ethology, we should eventually mention behavioural science. This community not only employs ever new technologies as observational tools and for data analysis, but even recognises that research in this field often lacks a more formal approach [35]. BMI as the mediating field should aid in bringing the AI methodology for data analysis to the behavioural sciences, while the latter would stimulate further research at the formal but also sensory level. A couple of investigations can already be found that deal with genuinely ethological issues concerning both animal behaviours [16,18,20] and behaviours of humans [21,29,30,32,43].

One important issue, we must not oversee, is that in almost all discussed areas privacy concerns are to be considered. Ethical issues arise and have to be carefully taken into account. For instance, [2] argues for an approach which emphasises communication in the design and implementation of monitoring systems, allowing to find an acceptable balance between potential abuses and benefits.

## 4 Conclusions

BMI is the computational advancement of ethology that automates the gathering of data, data analysis and even data interpretation. Some of the used methods, including knowledge representation and interpretation techniques, show how in particular AI aids in this automation process. In detail, BMI

- supports precise and comprehensive descriptions of behavioural phenomena,
- automates the whole evaluation of behavioural phenomena,
- can take into account background knowledge as well as complex relationships,
- mediates between observation and prediction, and
- brings together behavioural sciences with new application fields.

The latter includes, for instance, Ambient Assisted Living, Ambient Intelligence, Smart Environments and everything that helps to better deal with everyday life problems, in particular of the elderly and challenged people. Some specific examples demonstrate the added value of BMI in comparison to non-automatic observational tools and the shallow mapping of behaviours to interpretations:

- long lasting systematic observations of behaviours [3,18],
- taking into account temporally disjoint behaviour relations [17],
- measuring behaviours indirectly [12],
- learning typical patterns of behaviours [5], and
- the bottom-up $\leftrightarrow$ top-down interplay within the analysis process [1,36].

Such ingenious means for analysing behaviours show the first important steps towards a computational theory to ethology. Future efforts are necessary in order to enable a more common view on the different BMI layers and to allow arbitrary complex behavioural events to be considered.

## References

1. Aghajan, H., Wu, C.: From Distributed Vision Networks to Human Behavior Interpretation. In: BMI 2007, vol. 296, pp. 129–143. CEURS (2007)
2. Alder, G.S.: Ethical Issues in Electronic Performance Monitoring. Journal of Business Ethics 17, 729–743 (1998)
3. Andrienko, N., Andrienko, G.: Extracting patterns of individual movement behaviour from a massive collection of tracked positions. In: BMI 2007, vol. 296, pp. 1–16. CEURS (2007)
4. Augusto, J.C., Aghajan, H.: Editorial: Inaugural issue. Journal of Ambient Intelligence and Smart Environments 1(1), 1–4 (2009)
5. Aztiria, A., Izaguirre, A., Basagoiti, R., Augusto, J.C.: Autonomous Learning of User's Preferences improved through User Feedback. In: BMI 2008, vol. 396, pp. 87–101. CEURS (2008)
6. Boronowsky, M., Herzog, O., Lawo, M.: Wearable computing: Information and communication technology supporting mobile workers. it - Information Technology 50(1), 30–39 (2008)
7. Cohn, A.G., Hazarika, S.M.: Qualitative spatial representation and reasoning: An overview. Fundamenta Informaticae 43, 2–32 (2001)
8. Goshorn, R., Goshorn, D., Kölsch, M.: The Enhancement of Low-Level Classifications for AAL. In: BMI 2008, vol. 396, pp. 87–101. CEURS (2008)
9. Gottfried, B. (ed.): Behaviour Monitoring and Interpretation, vol. 296. CEURS Proceedings (2007)
10. Gottfried, B., Aghajan, H. (eds.): Behaviour Monitoring and Interpretation, vol. 396. CEURS Proceedings (2008)
11. Hallot, P., Billen, R.: Spatio-temporal configurations of dynamics points in a 1D space. In: BMI 2007, vol. 296, pp. 77–90. CEURS (2007)
12. Hein, A., Kirste, T.: Towards recognizing abstract activities: An unsupervised approach. In: BMI 2008, vol. 396, pp. 102–114. CEURS (2008)
13. Heitor, T., Tomé, A., Dimas, P., Silva, J.P.: Measurability, Representation and Interpretation of Spatial Usage in Knowledge-Sharing Environments. In: BMI 2007, vol. 296, pp. 43–61. CEURS (2007)
14. Hongeng, S., Bremond, F., Nevatia, R.: Representation and Optimal Recognition of Human Activities. In: CVPR. IEEE Press, Los Alamitos (2000)
15. Hotz, L., Neumann, B.: Scene Interpretation as a Configuration Task. Künstliche Intelligenz 19(3), 59–65 (2005)
16. Kaufmann, R., Bollhalder, H., Gysi, M.: Infrared positioning systems to identify the location of animals. In: ECPA-ECPLF, p. 721. ATB Agrartechnik Bornim / Wageningen Academic Publishers (2003)
17. Kiefer, P., Schlieder, C.: Exploring context-sensitivity in spatial intention recognition. In: BMI 2007, vol. 296, pp. 102–116. CEURS (2007)

18. Kritzler, M., Lewejohann, L., Krüger, A.: Analysing Movement and Behavioural Patterns of Laboratory Mice in a Semi Natural Environment Based on Data collected via RFID. In: BMI 2007, vol. 296, pp. 17–28. CEURS (2007)
19. Kurata, Y., Egenhofer, M.: The $9^+$-Intersection for Top. Rel. between a Directed Line Segment and a Region. In: BMI 2007, vol. 296, pp. 62–76. CEURS (2007)
20. Laube, P., Imfeld, S., Weibel, R.: Discovering relative motion patterns in groups of moving point objects. IJGIS 19(6), 639–668 (2005)
21. Martino-Saltzman, D., Blasch, B., Morris, R., McNeal, L.: Travel behaviour of nursing home residents perceived as wanderers and nonwanderers. Gerontologist 11, 666–672 (1991)
22. Merriam-Webster Online Dictionary. ethology (2009), `http://www.merriam-webster.com/dictionary/ethology` (visited on April 7, 2009)
23. Miene, A., Visser, U., Herzog, O.: Recognition and prediction of motion situations based on a qualitative motion description. In: Polani, D., Browning, B., Bonarini, A., Yoshida, K. (eds.) RoboCup 2003. LNCS (LNAI), vol. 3020, pp. 77–88. Springer, Heidelberg (2004)
24. Millonig, A., Gartner, G.: Shadowing – Tracking – Interviewing: How to Explore Human ST-Behaviour. In: BMI 2008, vol. 396, pp. 42–56. CEURS (2008)
25. Muller, P.: A qualitative theory of motion based on spatio-temporal primitives. In: KR 1998, pp. 131–141. Morgan Kaufmann, San Francisco (1998)
26. Musto, A., Stein, K., Eisenkolb, A., Röfer, T., Brauer, W., Schill, K.: From motion observation to qualitative motion representation. In: Habel, C., Brauer, W., Freksa, C., Wender, K.F. (eds.) Spatial Cognition 2000. LNCS (LNAI), vol. 1849, pp. 115–126. Springer, Heidelberg (2000)
27. Nagel, H.H.: From image sequences towards conceptual descriptions. Image Vision Comput. 6(2), 59–74 (1988)
28. Peuquet, D.J.: It's about time: A conceptual framework for the representation of temporal dynamics in GIS. Annals of Assoc. of Am. Geogr. 84, 441–461 (1994)
29. Pollack, M.E.: Intelligent technology for an aging population: The use of ai to assist elders with cognitive impairment. AI Magazine 26(2), 9–24 (2005)
30. Rüetschi, U.-J., Timpf, S.: Modelling wayfinding in public transport. In: Freksa, C., Knauff, M., Krieg-Brückner, B., Nebel, B., Barkowsky, T. (eds.) Spatial Cognition IV. LNCS (LNAI), vol. 3343, pp. 24–41. Springer, Heidelberg (2005)
31. Shi, H., Kurata, Y.: Modeling Ontological Concepts of Motions with Projection-Based Spatial Models. In: BMI 2008, vol. 396, pp. 42–56. CEURS (2008)
32. Shoval, N., Isaacson, M.: Sequence Alignment as a Method for Human Activity Analysis in Space and Time. Annals of Assoc. of Am. Geogr. 97(2), 282–297 (2007)
33. Sprado, J., Gottfried, B.: Semantic argumentation in dynamic environments. In: ICEIS 2009. Springer, Heidelberg (2009) (to appear)
34. Steinhage, A., Lauterbach, C.: Monitoring Mov. Behav. by means of a Large Area Proximity Sensor Array. In: BMI 2008, vol. 396, pp. 15–27. CEURS (2008)
35. Taborsky, M.: The Use of Theory in Behavioural Research. Ethology 114, 1–6 (2008)
36. Terzic, K., Hotz, L., Neumann, B.: Division of Work During Behaviour Recognition. In: BMI 2007, vol. 296, pp. 144–159. CEURS (2007)
37. Thirde, D., Borg, M., Ferryman, J.M., Fusier, F., Valentin, V., Bremond, F., Thonnat, M.: A real-time scene understanding system for airport apron monitoring. In: ICVS 2006. IEEE Computer Society, Los Alamitos (2006)

38. Timm, I., Scholz, T., Krempels, K.-H., Herzog, O., Spaniol, O.: From Agents To Multiagent Systems. In: Kirn, S., et al. (eds.) Multiagent Engineering. Theory and Applications in Enterprises. International Handbooks on Information Systems, pp. 35–52. Springer, Heidelberg (2006)
39. Van De Weghe, N., Bogaert, P., Cohn, A.G., Delafontaine, M., De Temmerman, L., Neutens, T., De Maeyer, P., Witlox, F.: How to Handle Incomplete Knowledge Concerning Moving Objects. In: BMI 2007, vol. 296, pp. 91–101. CEURS (2007)
40. Vu, V.T., Bremond, F., Thonnat, M.: A novel algorithm for temporal scenario recognition. In: IJCAI (2003), pp. 1295–1302 (2003)
41. Wagner, T., Bogon, T., Elfers, C.: Incremental Generation of Abductive Explan. for Tactical Behavior. In: BMI 2007, vol. 296, pp. 117–128. CEURS (2007)
42. Weiser, M.: The Computer for the Twenty-First Century. Scientific American 265, 94–110 (1991)
43. Winter, S.: Route Adaptive Selection of Salient Features. In: Kuhn, W., Worboys, M.F., Timpf, S. (eds.) COSIT 2003. LNCS, vol. 2825, pp. 349–361. Springer, Heidelberg (2003)
44. Wood, Z., Galton, A.: Collectives and how they move: A tale of two classifications. In: BMI 2008, vol. 396, pp. 57–71. CEURS (2008)