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# Product adaptivity through movement analysis: the case of the intelligent walk-in closet

### Abstract

In this paper we investigate the use of human movement qualities and the design of intelligent products. Our future products and systems are envisioned to become context-aware and adaptive. The design of these adaptive products brings new opportunities to the design of interactive products. Self-adaptivity of products depends on their ability to learn through interaction with the user. We explored a research-through-design process that revolves around a product which is able to interpret human movement qualities. In our approach we integrated three fields: Laban Movement Analysis, neural learning and interactive product design. In this paper, we explain our approach to design adaptive interactive products, and describe the resulting walk-in closet research platform. We present the choices and findings, show results of initial user-testing of the prototype, discuss the open questions that this innovative design approach raised, and further research possibilities.

### **Keywords**

Ambient Intelligence, Adaptive Products, Human Movement Qualities, Neural Learning.

### I Introduction

The integration of technology in our environment and in physical objects is envisioned to lead to ambient environments which are context aware, personalized and able to adapt and even anticipate our wishes, needs and behaviors [1]. This vision of Ambient Intelligence (Aml) leads to new opportunities in industrial design. Aarts and Marzano [1] noticed that self-adaptability of systems depends on how well the system can understand context and learn through interaction with the user. Our challenge was to integrate such ability into a product/system design process and to explore the design implications raised by this process. Several ways to analyze human behavior, based on nonintrusive sensors and wearable computers have been proposed [2,3,4,5,6]. They are based on the analysis of different modalities, such as, tactile modality [7] visual modality carrying information about facial expressions and body gestures [5,8], voice [9], facial, and head movements [10].

We explored an approach in which we recognize human movement qualities related to the whole body instead of facial expressions and gestures because of the inherent expressiveness of the human body. Exploitation of the rich perceptual motor skills of the user has been used before to derive mood or emotional state from the way people interact with a product [11,12].

Tracking and analysis of human body movement has yielded a large body of research on computer vision, for use in entertainment, sports, medical applications and in film making (see for instance [13]). Aiming at implementation of a body motion detection and analysis system within an everyday product, we need a system



**Fig. 1.** Visual representation of the novel combination of the three fields we integrated: LMA, neural learning and interactive product design.

that uses basic sensing technology, but is still able to recognize human movement qualities from simple movement measurements.

We use Laban Movement Analysis (LMA) to analyze the physical movement of the user because it combines a set of definitions which can help to distinguish different human states. LMA is a framework which can be used to describe and notate movement. Other research has shown that LMA can provide insight in human behavior and attempts have been made to implement this into product design [14,15]. LMA has also been used to describe frameworks which can be used to design dynamic product behavior, for example in the Choreography of Interaction design approach [16] and in the Interaction Quality Framework [17]. We explored the integration of a learning method in an interactive product/system in an everyday context. Our goal is to contribute to field of Aml from an industrial design perspective. We created a product that learns to categorize movement qualities of a person interacting with it. The designed adaptive product functions as research platform, creating the opportunity to further explore adaptivity in the design of Aml systems. For this purpose we integrated Laban movement analysis, neural learning and interactive product design (represented in figure one) into a product which is able to interpret the state of the user on a dimension which is useful in everyday practice.

A research platform was created (figure 2) using a research through design approach [18]. The goal of the

research platform is to investigate how the combination of movement analysis, neural learning and interactive product design can contribute to meaningful product behavior. We worked in close collaboration with a Certified LMA specialist [19] who helped us to become sensitive for the subtleties in LMA and was involved with important choices during the process regarding movement analysis. For neural learning we relied on unsupervised learning because of its ability to exploit the underlying structure of input data without any teaching [20].

The choice to design a walk-in closet platform was made, because a private space with a lot of movement is a good starting point to explore intelligence in the home environment. This platform follows a project at the Carnegie Mellon University School of Design [21], where a walk-in closet with lighting behavior was created. We extended this idea further by adding the interpretation of human movement qualities by the walk-in closet. The paper is organized following important phases of our research-through-design process. Section 2 describes how LMA theory was used to study the physical layout of the closet and how relevant movement qualities can be abstracted. In section 3 we describe how sensor data can be interpreted as movement qualities by the neural learning algorithm. In section 4 we will describe a preliminary experiment to test the implementation of the design. In section 5 we will elaborate on the design of the research platform. Section 6 is dedicated to the discussion which this study evoked and in section 7 will give our insights about where to take this research in the future.



Fig. 2. The finished walk-in closet which was designed based on the findings of the research through design process.

## 2 Integrating Laban Movement Analysis in the design

LMA is composed of five major components: Body, Space, Effort, Shape, and Relationship. Together these components constitute a qualitative language for describing movement [22]. We focused on the Effort factors since these are strong indications of human expression. For example, Quick movements point towards a hasty mindset of a person, whereas a Sustained movement relates to a relaxed mindset of a person.

Effort consists of four movement qualities: Space, Weight, Time, and Flow. Every movement quality is a continuum between two extremes which are: indulging in the quality and fighting against the quality. In LMA these Effort elements are seen as the smallest units needed in describing an observed movement. These Effort elements with their two extremes are: Space (Indirect/Direct), Weight (Light/Strong), Time (Sustained/Quick), Flow (Free/ Bound) [23]. In LMA the combination of two movement qualities from the Effort factors is called a State.

### 2.1 Influence of physical form on movement

Physical surrounding is one of the attributes which contributes to how people move and where attention is placed. This notion is deeply connected to LMA through for example the Space Effort [23]. To find out how the physical design of a walk in closet would change the movement of a person in the closet in terms of LMA Efforts and States we built two closets with different layout. The goal of this experiment was to find balance between the amount of movement which could be elicited from participants while maintaining efficiency in choosing garments. Within the first closet set-up (figure 3) the closet area is smaller and placed in one line, parallel to the walking area in the closet. In set-up two (figure 4) the closet has a corner in it, and the garments are placed with more space between them.

The participants acted out scenarios in the two different closet set-ups. For example a scenario was: you are in a hurry, get your tennis clothes. The scenarios used in the test were specifically developed, in cooperation with the LMA specialist, to elicit a variety of movement qualities from the participants.

After the experiment the video recordings of the scenarios were analyzed and coded in terms of movement qualities by two people trained during a oneday workshop in LMA and the LMA specialist herself. Based on these observations we concluded that closet set-up one gives a more consistent result in terms of movement qualities, while closet set-up two elicited more expressive human qualities. It was too early to find why this difference occurred. A conclusion for further development was that the physical design of the closet should be easy to modify to enable further testing of the influence of physical form on movement. A second conclusion from the test was to focus on the Space, Flow and Time Efforts. The Weigh Effort was not relevant for the proposed scenarios.

## 2.2 Abstracting and sensing relevant movement qualities

To interpret the human movement qualities of the user on a dimension which is useful in everyday practice, we aimed at abstracting parameters from movement which





**Fig. 3.** Set-up one within the test. The closet is placed in a line parallel to the walking area and the garments are placed concentrated.

Fig. 4. The second closet set-up used in the test. The closet is built around a corner and the garments are placed more spatially.

		Time	
		Sustained	Quick
Space	Direct	0	2
	Indirect	3	4

Fig. 5. The four combinations possible in the Awake state.

were unique enough to distinguish different behaviors of the user.

With sensors placed in the floor, in the shelves and in the vertical space in the walk-in closet we asked participants again to act-out several scenarios. From the analysis of the sensor data it became apparent that the walking movements and the movements of the participants in the shelves were most informative. These two movements related to two kinds of movement analysis: micro analysis of the movements in the kinesphere of the user (personal space surrounding a person) and macro analysis to describe the larger movements in the space.

We narrowed down the analysis of movement qualities to Space and Time Efforts to reduce complexity and because qualitative observation by the LMA specialist of the video recording showed that and sensor recordings were most distinguishable for these two Efforts. A combination of the Space and Time effort can be described as the Awake State. Because every Effort consists of two extremes it possible to create four different combinations of the Awake State (figure 5). **2.3 Scenarios to elicit Awake state variations** For every combination of two movement qualities of the Awake state one scenario was created which could be used to elicit these specific movement qualities from a person. All the scenarios had as main context a selection of clothes for different occasions, but the feeling (for example stressed or relaxed) was varied.

- Sustained/Direct: It is a Sunday evening; you had a nice and easy day. Tonight you will have a drink with a friend. You have the time to prepare your clothes, you are very relaxed. You already know what to wear, you want to wear your favorite party clothes tonight to feel comfortable. Take your favorite party clothes, you have all the time in the world.
- 2. Quick/Direct: It is Friday evening. You had a long day at school, and you just returned home. You receive a phone call: "hey, do you want to join us for a drink tonight?" You quickly finish dinner, and rush to your walk-in closet. You are going to party tonight and you will be picked up in 10 minutes. You will take your favorite party clothes tonight, hurry!
- 3. Sustained/Indirect: It is a Saturday evening. You had a quite relaxed day and you are looking forward to tonight. Last week you and your friends decided to go partying tonight. You are going to your walk-in closet and take your time to choose clothes. It is a special occasion to be together with so many friends, so take your time to choose nice clothes.
- 4. Quick/Indirect: It is Saturday evening. Today you worked at your part-time job, it was a long day but you still feel full of energy. You call your friend in Amsterdam and ask if she wants to party tonight.

She agrees to join, and you decide to go to Amsterdam. You will have to leave in 10 minutes to catch the train! You want special clothes for this special occasion, so you decide not to wear your favorite clothes. Choose a set of clothes, but hurry!

**3** Integrating neural learning in the design Martinetz and Schulten [24] have devised an algorithm which is able to reduce dimensionality and reveal the structure from a dynamically changing input set of data, the so called Growing Neural Gas algorithm. We used the simpler Neural Gas algorithm to analyze the abstraction of movement data from our sensors, in a way similar to [20] and to find data structure which can be linked back to movement qualities in Laban terminology.

To enable the neural gas algorithm to find relevant structures in the input data we need to record data which has a relation with the movement qualities that we want to discover. First these recordings function as training data for the algorithm to divide them on classes and secondly the algorithm uses these classes to cluster the new coming data.

The layered conceptual framework for expressive gesture applications of Camurri et al. [25] describes different layers which can be used to analyze movements (illustrated in figure 6). We used this framework as guidance to process raw data to a meaningful interpretation about the state of the user on a dimension useful in everyday practice.

### 3.1 Interpreting movement patterns

In the framework of Camurri et al. (figure 6) the first layer is the acquisition of physical signals. Our approach to interpret human physical movement was to use relatively simple sensors, which placed on appropriate positions in the closet are able to capture unique information to distinguish the intended movement qualities. To capture macro movement we placed 12 sensor mats (595mm x 170mm) in the floor which are



**Fig. 7.** The prototype set-up: in the shelves six passive infrared sensors. On the floor 12 sensor mats which can switch between on and off state.

able to capture the walking movement on one axis. In the shelves we placed six passive infrared sensors which measure activity, which we linked back as micro movement. An illustration of the set-up can be found in figure 7.

This raw data can be considered as physical signals, but the parameters which can be calculated from this data as for example speed can also be considered as a layer I variable. The sensors were connected through three Arduino microcontrollers [26] to a PC. Calculations were made with Cycling '74 Max/MSP [27]. Layer 2 of the framework explains how statistical parameters are calculated to create specific motion cues. We implemented this, for example, by calculating the percentage of movement with high acceleration during the total interaction with the closet. In our system we use the 3rd layer of the framework as a step where the training set for the learning algorithm is created. These training sets can be composed from any combination of parameters from the first and second layer. We found out that the quality of the interpretation by the neural gas network depends on how the training sets are composed.

The interpretation of the Laban States takes place in the 4th layer. The neural gas algorithm is able to find structures from the training sets after a training session





of 10 times 5 seconds and can cluster training sets based on these structures. When the sensor sources are chosen well, the clustering information can be related back to Laban movement qualities. The algorithm was implemented in Java within a Max/MSP object.

## 4 Experiment to test the interpretation of movements

With a user test we were aiming to find out if the prototype we developed in the preceding iterative process was indeed able to interpret the human movement qualities of the Awake state. In figure 8 the closet prototype as described in section 3 is pictured. The system was trained with training data compiled from 2 people who were trained in LMA during a one day LMA workshop, the same training set was used during the whole test. The test consisted of 10 male participants, chosen using convenience sampling, who acted out the scenarios to elicit different extremes of the Awake State Efforts as explained in section 2.3. The scenarios were read to the participants, after which the participants were asked to act out the scenario as good as possible. Video was recorded of the participants, while the interpretation data of the algorithm was also recorded.



Fig. 8. The closet set-up with all the sensors integrated.

### 4.1 Discussing the results of the experiment

We compared video recordings with the interpretation data of the algorithm. Analysis by the LMA specialist indicated that the interpretation of the Space Effort of the closet is reasonably in line with the observation from the video. We tentatively conclude from this that the most informative movement quality was the Space Effort. There was a difference in interpretation of the system for different user test participants. Some participants used more Indirect movement throughout the entire scenario, while others used more Direct movement. A possible explanation for this outcome is that the system was able to interpret the difference in specific movement styles of the participants. Another explanation is that the initial training session by the two persons was not personalized enough and worked for some participants, but failed for those with a different movement style. Further study is needed to be able to explain this phenomenon.

### 5 Towards a research platform

The experiment described in previous section raised many questions and it is difficult to draw strong conclusions. However, the process leading to the walk-in closet prototype and the experiment lead us to believe that further research can unveil interesting results. We have chosen to create a research platform which will enable us to conduct further research on the integration of the fields of LMA, neural learning and product design. Such a platform should communicate the intelligence and adaptivity through its form and behavior.

#### 5.1 Physical design of the closet

The prototype we used for the experiment (pictured in figure 8) looked like a very traditional closet. However, when interacting with it, the closet's behavior is not traditional at all, it is intelligent.

Therefore, the embodiment of the closet needed a drastic change, and was designed to be perceived as intelligent, and communicate the nature of the closet through the physical form. The shelves of the closet communicate this through the body line, adaptivity, complexity, dynamics, and cleanness of form. These aspects were influenced by the movements made by the users, resulting in the final prototype which is pictured in figure 2.

In order to study the relation between adaptivity of the product behavior and its physical constitution, the closet was designed as modular system. We ensured that the sensors and actuators could easily change their position and different sensors and actuators could be added. The set-up of the closet (the embodiment) was also modular as each shelve can easily be attached and detached to the wall. Different set-ups can therefore be easily created and tested. For example the set-up picture in figure 2.

## 6 Conclusion

In this paper we described the research-driven design of a platform for investigating different aspects of the interaction between an intelligent interactive product and a person. We integrated three separated fields, and this combination triggered many questions, points of discussion and new research opportunities. It was deliberately chosen to stay on the level of Laban Movement Analysis and to create scenarios which were linked to movement gualities. We focused on the analysis of Space and Time Efforts to reduce the complexity of the analysis. This limited our system in the ability to interpret more complex human movement behaviors. Based on the initial and the ongoing user tests we concluded that interpretation of movement qualities can be one of the factors which an AmI system can take into account to adapt better to its user. The better the system can understand LMA and interpret movement qualities, the better adaptation to the user will take place.

There is still room for further optimization of the current analysis of the Space and Time Efforts. In the third layer of our implementation of the Camuri et al. [25] framework the training set data for the learning algorithm is created. This training set is composed from a combination of parameters from the first and second layer during a specific time frame. Finding an optimal combination of parameters will improve the effectiveness of the learning algorithm further. We have implemented unsupervised learning in the system. The benefits of unsupervised learning are the robustness and flexibility of the algorithm; structures which cannot be known a priory can be found. However, this method requires a human to add meaning to the system clusters. We now added this meaning to the clusters manually after the training was completed and clusters were found. Supervised learning could be considered as alternative, because this method can interpret training set data following learned information. The interpretation is based on predefined structures.

### 7 Discussion

The research platform we developed triggered a myriad of new research directions for the field of product design, adaptive products and Aml.

Specifically aimed at the context of choosing clothing new opportunities arise. The openness and changeability of the research platform leaves room for further explorations and experiments within this field of design. A design possibility could be to help the user to reflect on the choice of garment by providing a "light trail" of movement history. Besides the home-context a translation could also be made to a shopping context. The information from movement qualities of the customer could be used by shops to more purposefully present products to their customers.

A value of human movement analysis by a system is the consistence of interpretation. This could be used when a product needs to be evaluated though user validation. Instead of relying on questionnaires, the categorization of the system can be used to measure the effects of a design on the user in terms of movement gualities. Being able to interpret the human movement qualities is an useful step towards designing product adaptivity. This new knowledge of the user can be used by the product to react with more meaningful behavior. The behavior can be purposely designed to adapt on specific movement qualities (for example reacting on a hasty user with more efficient task lighting). We think that LMA can also have potential to when designing dynamic product behavior. The interaction with a product which behaves using movement gualities derived from LMA could be perceived as more natural for example. LMA specialists are able to use movement qualities to elicit reactions from people on subconscious level, for example when training politicians. The possibility to design an intelligent product which is able to purposefully influence the behavior of a person presents new research opportunities. Many questions arise when we think about implementing this into intelligent products. What happens when we design an intelligent closet which is able to elicit more relax movement when the user is behaving hasty for example? Besides new research opportunities this new ability of intelligent products also raises many ethical questions.

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