# **Grip Sensing in Smart Toys:** A Formative Design Method for User Categorization

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## Abstract

Modern toys are interactive, motivate play, and can be used to aid detection and analysis of play behavior. Our research has investigated the use of wireless sensors embedded in toys to aid in the automatic detection and analysis of children's playtime activities. In order to guide age appropriate interaction style and facilitate data collection (adult vs. child), we need to identify who is playing with the toy. This becomes especially challenging when these smart toys are deployed into everyday play areas. In this paper we describe a formative design methodology to inform the creation of a smart toy that could allow differentiation between a child and adult. We also describe an evaluation of our prototype design from a pilot study that shows promise for future research.

#### Keywords

Activity Recognition, Toy Design, Object-Play, User Categorization, Play Behavior, Autism, Developmental Delay, Cognitive Conditioning, Sensors, Affordances

## ACM Classification Keywords

H3.1. Content Analysis and Indexing;

## **General Terms**

Design, Experimentation, Human Factors, Performance

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## **Introduction & Motivation**

The play behavior of a child while interacting with a toy can serve as an early indicator of developmental delay [1]. Interactive toys can be used as playmates which influence the learning process of the child [12].

*Child'sPlay*[2] is a project that uses smart toys with wireless sensors (accelerometers) to help gather play behavior information which, in the future, may be used by researchers to help identify developmental delay in children. Some of these toys are also capable of identifying intentional vs. accidental interaction by detecting proximity through capacitive sensing [5]. Given the chaotic activity during playtime, the ability of the toys to capture play motion data and identify intentional play provides significant information. However, the data is still incomplete when one considers the social and interactive nature of play. Play often involves turn taking between parents, siblings or adult care givers and the child. In addition to recording quantitative measures about how a toy is manipulated, it is also important that the toy be able to identify who generated the data. User identification is necessary in order for the system to tag only the datasets relevant to the child as well as highlight higher levels of social play that are key in identifying developmental delays. Inability to tag child-user generated data can result in datasets which quickly overwhelm the analyst with copious amounts of data that may or may not be relevant.

In this paper we describe the design process used to develop a toy that can discriminate between users based on presumed categories (adult vs. child). We chose a categorical level of identification primarily due to economics. While advanced sensing—such as highresolution multi-touch sensors [3]—could presumably allow for the discrimination between individuals, the current costs of such a platform were too high or were not accurate enough to provide sufficient user identification. In general, the design of our system would have to conform to the following goals:

- The toy must adhere to child safety standards.
- Must be robust to withstand rough play.
- Must optimize sensor placement to achieve the goal of user categorization.

#### Approach

Our toy design considers children in the age group of 12-24 months as the primary users of the toy because the Child'sPlay system currently supports this target population. However, the approach we present here (toy design with surface "grip" sensor placement) can be generalized to other toy designs targeting various age groups.

Research projects have focused on grip abilities and sensing [4,5,6] as well as affordances of artifacts in the context of ubiquitous computing [7]. An exploitable difference between a child and an adult is the manner in which an object is gripped. Adults tend to adhere to the advanced affordances of the object while children, especially ages 12-24 months, tend to grip objects according to developing cognitive conditioning, motor and dexterity capabilities [8]. Secondly, there are visible differences between an adult and a child grip in terms of the breadth and depth of the grip on an object and the overall surface area covered. It is these two facets that we used to design a toy that best enables adult-child differentiation. In order to derive meaningful differentiation between the adult and child we aim to persuade an adult user to interact with the object in a particular way based on positive and negative affordances. While a child will interact with a toy in many different ways, an adult's interaction yields more stereotypical gripping patterns that can be used to positively identify an adult user.

## **Toy Design**

We chose to design a fish because of the simple nature of the body and the interaction styles it will afford. This fish, we like to call it "Spotty," has the following design and technology elements:

- The shape of the fish provides an excellent affordance; it has tapering ends while the center of the fish body provides the girth for a natural grip zone. This feature provides an adult user a place to grip. This also allows the placement of sensors in a limited area as opposed to having to spread them out throughout the body of the toy.
- Features on the fish such as eye balls, mouth etc. act as negative affordances and discourage adults from grabbing those regions.
- Color and sound augmentations to the toy appeal to children and encourage interaction with the toy. Future versions of the toy will be brightly colored and make a rattling sound on motion.
- FSR pressure sensors are used to register the grip patterns on the surface of the toy. The choice of sensors was made due to the robustness and cost effectiveness of the FSR sensors. The sensor placement on the fish body is informed by the user grip study that we conducted. This study, as explained below, helped identify hotspots and grip zones on the body of the toy to achieve optimal sensor use, a total of 16 sensors, 8 on each side.

 The core of the sensing platform is an Arduino [9] board which reads the input from the FSR pressure sensors to derive grip patterns and the BlueSense [10] sensor package for the simultaneous sensing of acceleration and capacitance [11].



Figure 1: Spotty, the fish.

# Formative User Study

*Exploration of presumed affordances* We ran a field study with the first prototype of the fish toy (not pictured) with a group of adults who engaged in mock play as if they were trying to get the attention of a child. Around 20 users participated in this study and it confirmed the presumptions we had about stereotypical adult interactions. The users demonstrated a good degree of conformity to the expected behavior due to affordances such as body shape and surface markings, described in the above section, in the handling of the toy.

## Hand Grip Study, Sensor Placement

The toy had to be large enough to accommodate the sensor system within it, but a larger toy would also cause an adult to grab the toy in a more-or-less consistent manner. The goal is not to ensure the same grip across all instances of adult interaction, but to reduce the kinds of interaction to the point that the one can deduce whether or not the user is likely an adult.

We designed a grip study to better understand the ways an adult might grip the toy as well as to map the positions of adult digits across the surface of the toy. While we have not found anything in the literature that directly mimics the following methodology, we were inspired by the idea of ink blotting that one may experience sitting in the dentist chair to align teeth.

We had to devise a way to capture the placement of an adult hand on the toy and then aggregate the data. Five adults (1 left-hand, 4 right-hand dominant) were asked to participate in a study. First, a 4 x 8 inch sheet of semi-transparent paper was wrapped around the toy. To this paper, a reference mark was applied that corresponded to reference marks on the toy. These marks ensure that each piece of paper could later be aligned and overlapped like they were on the toy and thus allows cross-comparison and aggregation later.

Next, we asked each participant to dust their dominant hand and grab the toy in any manner they preferred but as if they were going to show it to someone else or a child. The dust we used was a mix of graphite powder and corn starch as this seemed the least "dirty" or, in other words, inhibited the user less than other kinds of marking, such as ink or oil. The participants usually held the toy and animated it as if it were a fish swimming. After the participant set the toy down, the paper blotter was removed and a new sheet was applied. This was repeated until five trials were successful. The hand of each participant was outlined for later reference and anthropometry. We acknowledge that five participants is a very small sample to infer data reliably but we believe the methods are justified and suggest that future studies include a variety of hand sizes and dexterity types.

Once the data were collected, each participant's data were aggregated by sketching the fingerprints onto a new sheet of paper one on top of the other (figure 2).





Then each of the individual aggregates was sketched onto another new sheet of paper using a threshold limit. The threshold is set to be only regions where a participant's fingers touched the same place on the toy more than twice. Finally, regions in the threshold where multiple participants' grips overlapped determined the hotspots for the placement of the FSR sensors on the toy (Figure 3).



Figure 3: Left to Right: Total, Threshold 1, and 2

The final threshold (Figure 4) shows a surprising regularity between digits. While we expect that sensor placement may not be as uniform given more trials across more participants, we find this result interesting, and believe that no matter the final results, this approach would provide a good sense of where designers should place sensors.



Figure 4: Threshold 2, Highlighted in Pink

## Discussion

The data collected from the 8\*2 FSR sensors is parsed into a 4\*4 matrix which is bi-cubic interpolated and represented as a heat map. The first two rows of the matrix correspond to the eight sensors on the left side of the fish, and the last two rows of the matrix correspond to the sensors on the right side of the fish (Figure 5).

It is important to note that the system is designed to identify adult grip with highest possible accuracy. With the adult user's data footprint tagged, all other intentional play data is associated to children. It is possible that an adult user's interaction could be classified as child data, but such anamolies may be acceptable when combined with other sensing information.



Figure 5: Visualization of grip data from FSR sensors

The combination of the motion data from the accelerometers and the grip pattern data from the FSR pressure sensors provide sufficient data to enable the differentiation between an adult and a child user.

### **Future Work**

We believe this is only a small move toward solving the user identification problem in smart/interactive toys and there is much work ahead of us. Yet, the research approach we present here shows potential for future work. The following is a list of possible directions.

- Our formative research needs to develop further before the methods we described are reliable for sensor placement and user categorization. We have not yet shown that given a user interaction that we can reliably discriminate user categories.
- We want to extend our methods to achieve individual user identification that do not use methods such as RFID tagging of users, but differentiates according to grip.
- Further development of accurate pattern recognition and capture.
- Consideration of supervised machine learning methods that can be applied to help in recognition of grips, especially in the case of deploying the toy in a household or controlled scenario with finite set of identified people who will come in contact with the toy.

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#### **Example citations**

[1] Baranek, G. T., C. R. Barnett, E. M. Adams, N. A Wolcott, L. R Watson, and E. R Crais. "Object play in Infants with Autism: Methodological Issues in Retrospective Video Analysis." *American Journal of Occupational Therapy* 59, no. 1 (2005): 20-30. [2] T. Westeyn, J. Kientz, T. Starner, and G. Abowd "Designing Toys with Automatic Play Characterization for Supporting the Assessment of a Child's Development" *Workshop on "Designing for Children with Special Needs" at* IDC 2008.

[3] Rosenberg, I. and Perlin, K. 2009. The UnMousePad: an interpolating multi-touch forcesensing input pad. *ACM Trans. Graph.* 28, 3 (Jul. 2009), 1-9. DOI: 10.1145/1531326.1531371

[4] Buttolo, P. 1996. Characterization of Human Pen Grasp With Haptic Displays. PhD Dissertation. University of Washington.

[5] Singleton, W.T. 1982. The Body at work: biological ergonomics. Cambridge, University Press.

[6] Pheasant, S. 1992. Bodyspace: anthropometry, ergonomics and design. Taylor & Francis.

[7] Sheridan, J. and Kortuem, G. (2006) Affordancebased Design of Physical Interfaces for Ubiquitous Computing Environments. Proc. of the 2006 International Symposium on Ubiquitous Computing Systems (UCS 2006)

[8] Shaperman, J., LeBlanc, M. 1995. Prehensor Grip for Children: A Survey of the Literature. Journal of Prosthetics and Orthotics, 7(2) pp. 61-64.

[9] http://www.arduino.cc/

[10] Presti, P. "BlueSense - A Wireless Interface Prototyping System." Master's Thesis, College of Computing, Georgia Tech, Atlanta, 2006.

[11] Tracy Westeyn, Peter Presti, Scott Gilliland, Jaisheng He, David Quigley, Jeremy Johnson, Thad Starner "Capacitance Sensing in Smart Toys: Aiding the Detection of Play Behaviors" at Ubicomp 2009.

[12] http://beatbots.net/research/