Affecta-Context: The Context-Guided Behavior Adaptation Framework

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Abstract. This paper presents Affecta-context, a general framework to facilitate behavior adaptation for social robots. The framework uses information about the physical context to guide its behaviors in human-robot interactions. It consists of two parts: one that represents encountered contexts and one that learns to prioritize between behaviors through human-robot interactions. As physical contexts are encountered the framework clusters them by their measured physical properties. In each context, the framework learns to prioritize between behaviors to optimize the physical attributes of the robot's behavior in line with its current environment and the preferences of the users it interacts with. This paper illlustrates the abilities of the Affecta-context framework by enabling a robot to autonomously learn the prioritization of discrete behaviors. This was achieved by training across 72 interactions in two different physical contexts with 6 different human test participants. The paper demonstrates the trained Affecta-context framework by verifying the robot's ability to generalize over the input and to match its behaviors to a previously unvisited physical context.

1 Introduction

The physical context of our interactions with fellow humans has a significant influence on our behavior. We shape our behavior through continuous interactions with the environment. We moderate different aspects of our behavior with each physical context we encounter [1]. For social robots, the physical context may pose a challenge for them to communicate effectively [2]. The physical intensity, the proxemics, the audio volume, and the amplitude of movements are all examples of adaptable parameters that can in or decrease a robot's ability to communicate. If these are not attuned to the physical demands of the context the robot may not be able to communicate effectively. As an example, a loud speaking robot can be heard at all times but would probably be a terrible fit for more intimate interactions.

When social robots are designed they are usually equipped with a set of discrete behaviors to handle a variety of social interactions. While such robots are well attuned to specific contexts, placing them in a different context can make some of their actions seem inappropriate. This could introduce a negative effect on the social capabilities of the robot. English & Carstensen 2014 discuss that the humans in human-robot interactions determine the amount of affective impact from the robot's actions. This complicates a dynamic adaption to contexts for robots further - as every human evaluates its actions from a different perspective, making certain actions more effect-full at certain times in specific contexts [3]. Also, the social, cultural, and physical contexts are important for the robots because we humans interpret their actions in light of the context in which they are performed [4].

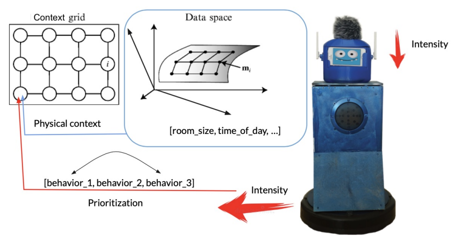

Fig. 1. The Affecta-context framework: Each physical context is represented by areas in the context-grid (left). Each area is represented by its physical attributes such as physical proportions, terrain, etc. (middle). For each context, there is a set of behaviors ordered by how well they match the context (bottom). The Affecta-context framework guides the physical intensity of the robot ensuring it matches the robot's current context (right).

If the physical setting is known ahead of an interaction it may be viable to pre-define the best fitting behaviors. However, It is often not the case that robots possess sufficient information ahead of interactions, and there is also no guarantee that the predefined physical proportions pertaining to a specific scenario or user preference remain valid throughout a whole interaction. This underlines an argument for using dynamic learning strategies as Weber et al. 2018 suggest by adapting a robot's humoristic behavior to specific user preferences [5]. Some contextual information may also be unattainable ahead of an interaction. For instance, the expected affective impact on humans (how much the current interaction changes the current affective status of those that interact with the robot) may vary with different robot morphologies, different cultural contexts, etc. This paper argues that it may be beneficial for social robots to continously learn the affective impact of behaviors in specific physical contexts along with open-ended discovery of new environments and it presents a framework to facilitate this.

1.1 Previous approaches

Adapting behaviors to the context has been found effective as a driver for more diverse behavior choices in social robot projects, and developing context-aware systems may be the hurdle to overcome to unlock better social functionality of robots outside of lab conditions [6,7]. There have been a few projects on optimizing robot capabilities according to the physical context. Narayanan et al. 2011 created movements based on visual perception of the environment and Jamone, Damas, and Santos-Victor 2014 created dynamic mapping models based on interactions with various objects [8,9]. The models in the latter allowed the robot to approximate the torque rate for correctly interacting with different context objects. Pandey et al. 2010 created a framework that paid special attention to humans as objects in the vicinity as their navigation system analyzed local clearance and environment structure [10]. The acoustic properties of environments were used in Lera et al 2017 to classify indoor contexts [11]. The project investigated using convolutional neuronal networks to classify different contexts based on ambient audio signals. Xiao et al. attempted to increase the contextual knowledge of a robot in interaction by allowing communication through natural body language. The robot they created could understand the meaning of human upper body gestures and would communicate by using movements, facial expressions, and verbal language [12]. Robots that autonomously determine the personality traits of the users were the focus of Zafar et al. 2018 and Zafar et al. 2019. Their solution used speech characteristics and found promising results in detecting personality traits [13, 14]. Their approach used excerpts from the interactions annotated by a psychologist to link nonverbal cues to a level of exhibited extroversion. A common link in these projects is that they investigate the adaptation of robots and robot behaviors to specific physical attributes in an environment. This is often achieved using individual context representations tailored to each specific task environment. This project aims to extend this research and develop a general context-aware framework that utilizes multiple forms of contextual information to adapt discrete behaviors to the current physical environment. The framework we present offers dimensionality reduction which allows it to be used with any number of different attributes to represent each context. This allows it to be used with both simple and extensive sensor setups.

1.2 Context-based behavior selection

In this paper, we present Affecta-context, a general framework that provides context-guided behavior selection across multiple physical contexts. The framework gradually learns to prioritize between a set of discrete behaviors in accordance with the robot's current environment, utilizing a combination of preconfigured behaviors and dynamic learning strategies. Behavior selection is optimized over multiple visits to physical contexts and is evolved as the robot explores and visits new contexts. The framework places all visited contexts in the topography of nodes - each representing currently known contexts. As more contexts are visited, Affecta-context generalizes on the input and clusters similar context nodes in the vicinity of each other. As the robot encounters humans in each context, it interacts with them and attempts to verify the affective impact of one of its discrete behaviors. The visible and audible reaction of the humans that interact with it determines the fitness of the behavior. The Affecta-context framework was added to a robot and trained in 72 different interactions with 6 human participants across two different physical contexts. The Affecta-context framework enabled the robot to distinguish between the individual contexts and created a prioritized set of behaviors as per the users' preferences. Through the participants feedback, a high-intensity level behavior was determined more fitting for the robot in a physically large room of 6x5m, while a lesser intensive action was found more appropriate in a smaller room of 2x3m. A validation experiment placed the robot in a new physical environment and had it identify the optimal matching discrete behavior. This identified behavior was verified as being the best fitting behavior by a group of human observers to a significant extent (n=90, $p<.05$) through an experiment demonstrating the optimal vs randomly selected behaviors. Although the framework presented in this paper simplifies complex human affective processes, the results indicate that it can provide a good foundation for projects on non-preconfigured affective behavior control. It is scalable in that it offers dimensionality reduction and may be used on multiple measure-points defining the context.

2 System overview

The robot we used is a 75cm tall mobile humanoid robot. It was constructed by extending an open-source version of iRobots Roomba robot that provided a base to build upon and movement [15]. Communication with the platform was done through FTDI via a serial connection input. The main system and context representation was running on a raspberry PI, while a camera sensor, text to speech recognition, and facial and body- recognition algorithms were running on an iPhone connected to the raspberry pi through USB via the peertalk interface [16]. The phone also utilized the apple neural engine to process the facial expression of the users to classify their current affective state using a pre-trained convolutional network as used in Levi 2015 [17]. The phone also provided a display to show the facial animations of the robot. This allows it to display a variety of different predefined expressions [18]. The robot has three contact sensors placed at the front bumper of the robot. It also has three low-range distance sensors, one at the front and one on either side. For actuation, the robot uses two electric motors in a differential drive setup allowing the robot to move forward, backward, and to turn around its center axis. The robot can be seen in Figure 1.

2.1 Context representation

A vital part of the Affecta-context framework is a representation of the different contexts. In the framework, each context is represented by a single vector that holds all attributes that define each context. As an example, each feature vector may hold values for the estimated room size, ceiling height, encountered obstacles, and further attributes that can be used to distinguish the physical context. The affecta-context framework holds a collection of multiple feature vectors, one for each encountered context. It provides dimensionality reduction for these context vectors and attempts to arrange them so that similar contexts are placed near each other. The data structure we created is inspired by a self-organizing map (SOM) which can cluster similar vectors in the topological vicinity of each other [19]. Each of these topological positions represents a single physical context and the topological placement of them represents small variations in the physical attributes, meaning that a single context may take up more than one topological position and carve out an area of the representation. The data structure we created also allowed the framework to define individual attribute weights (see details below) and to provide a direct input-to-topological-position method.

Any number of physical attributes can be used to represent the context. For simplicity in this paper, the robot in this paper would use the physical size of the environment estimated with simple average-time-of-drive values in each physical context. The context representation provides dimensionality reduction like a regular self-organizing map and with richer sensors available, multiple physical characteristics could be sampled to give a more precise representation of the current context in each feature vector. The context-grid at the left side in Figure 1 illustrates the topology of context nodes while the dataspace depicted in the middle illustrates multiple attributes that define a physical context. The number of attributes used to represent the context defines how detailed the representation is.

2.2 Updating the context representation

The context-representation consists of 100 different physical contexts arranged in a 10x10 matrix of individual contexts with an area of 2d positions for each of them. The matrix is initialized with a context vector for each position and the attribute-values of these vectors start randomized between 0 and 1. Each time new contexts are explored and new context-vectors are created, the most similar context-vector in the matrix is retrieved and each measuring point in this context-vector is updated by the difference between each value modified by a learning rate. The distance between context-vectors is defined as the sum of the squared difference between all context attributes of the vectors multiplied by an attribute-specific weight modifier. As the closest matching context-vector is updated, the nearest contexts in the euclidean distance around it are also updated with a learning rate that decreases (halves) with each distance step away from the center context-vector. In a similar style as self-organizing maps, introducing a fundamentally different new input vector automatically creates a new region representing a context, in the topology of the 2d matrix by altering the existing context vectors. In our implementation, the distance between context-vectors is furthermore calculated with attention to the importance of each of the gathered measurements in it. Some measure points may be more important than others and could have a greater impact on similarity when determining the distance between contexts. To model this, each measuring point in a context vector has an added importance modifier that multiplies the difference value.

2.3 Behaviors in a context

All individual contexts represented in the 2d matrix have a set of behaviors attached. These are ordered in priority after the best fit for the specific context. The behaviors consist of a series of movements (forward, backward, and turning movements), head antenna gesturing (waving pattern), facial expression animations, and audio expressions. Each behavior differs in audio and animations but shares the same movement and gesturing patterns at different intensity levels from 0 to 3, meaning that each of the four behaviors has a unique intensity level. The intensity level defines the size of the physical movements and gestures, and also determines the intensity of the animated expression. The highest intensity level at three has the largest movement and gesturing actions while intensity zero does not have any movements or gesturing but instead consists solely of animations and audio expressions. The robot prioritizes between behaviors of the context by testing them through interactions with humans, and by gradually adjusting its prioritization for the identified physical context of each encounter. The behavior priority for each context is updated with the same strategy as the physical context-vectors with the behaviors of the neighboring contexts being updated with a decreasing learning rate as well. The topology of the nodes may be altered when new contexts are discovered which indirectly influence the behaviors prioritized in similar contexts.

3 Experimental setup

The framework was trained in two separate phases followed by a validation experiment to investigate the abilities of the trained framework. During the first training phase, the robot would explore two different phsycial contexts after which it was manually verified that the robot was able to autonomously create discernable representations for each of the indentified contexts. With the second training phase the robot attempted to define the affective impact of the four discrete behaviors. This was done through interactions with human participants.

3.1 Training Phase One: Physical context exploration

The initial training phase used the framework in two different physical contexts, a 6x5m living room, and a 2x3m bedroom context. The robot would randomly explore and gather measurements for a total om five minutes in each context while simultaneously updating its context representation. This was achieved by moving around in random directions until the robot had performed 3 successful measurements of time-of-drive in the physical space. The created context representation was manually validated by expecting the visualized context-representation in relation to the average time of drive measure point as seen in Figure 2. In that visualization it can been seen that the robot creates areas in the context-representation to represent each context and contexts that have similar attributes (similar physical values e.g. physical size). The free available space may be smaller in either of the two test locations. The framework accounts for that automatically as it measures the available space.

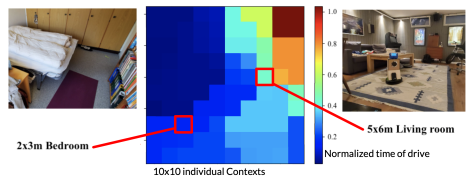

Fig. 2. The physical context representation after 5 minutes of exploration in each context. The 10x10 squares represents the individual contexts, and each color represent the normalized time-of-drive measurement values from 0 to 1. The highlighted areas shows the individual context representation for each training context. The similar neighburhood colors shows that the framework is on the way toward creating a niche area for each of the two contexts in the representation. Note that this map shows the context representation, not a map of the physical location.

3.2 Training Phase Two: Behavior prioritization

The second training phase focused on developing a prioritization between behaviors in each context in regards to information gathered in human-robot interactions. The robot would interact with 6 different test participants (recruited with informed concent). The training sessions were performed in the two different physical contexts. The human participants would interact individually with the robot one after another from a similar proximity between 1 and 2 meters. Each interaction lasted for about ten minutes and the participants were offered a chair to sit on if they felt like it. The participants were informed that the robot would interact with them as soon as it could see them. They were not instructed to perform any specific actions other than to interact with the robot and answer truthfully to any questions it would ask them. With each participant the robot would initiate a conversation and ask to the participants to determine the best of two randomly selected candidates for behaviors that would fit the current physical context. The learning strategy for this behavior selection across the various interactions followed a classic epsilon greedy reinforcement approach with an exploration part and a verification part (in a 4/1 ratio decreasing over time). The exploration path used a random behavior while the verification strategy would use and test the currently rated best-fitted behavior. The fitness number for each behavior was updated following the interaction and the sum of positive votes out of the total number of votes would define the behavior-rating for that specific physical context going forward. During the full range of training, the impact of 72 behaviors were investigated across the two contexts and 96 physical context measurements were gathered.

3.3 Validation Experiment: Autonomous behavior selection

We performed a validation experiment to verify that the chosen behavior-intensity of the robot in a previously unvisited context to a significant extent was also determined to be the best fitting behavior by human observers. The robot was given three opportunities to determine the best possible behavior intensity for its current environment. Each attempt included gathering three measure points and avering those to find the best matching physical context in the trained context representation. The changed physical context consisted of a 4 x 4m room that was chosen for its physical proportions occupying the middle-ground between the two previously visited physical training contexts. Although this was an already completed physical test-setup, the current COVID-19 pandemic forced us to move this interaction to Amazons online mTurk platform. We recruited 90 participants who each viewed a randomized video comparison between the behavior found most fitting by the robot and one of the other three included behaviors. With the presented videos we tried to give the participants as good as possible view of the physical environment and of the robot's behavior by placing the camera in similar positions as the participants would be placed in a real physical encounter with the robot. The participants were asked to determine which of the two behaviors they found most fitting for the robot's current physical environment. The participants were also also to rate how each behavior matched the current physical context on a likert scale from one to ten with one being "poorly matched" and 10 being "perfectly matched".

4 Results

4.1 Manual verification of the training phases

Figure 3 shows the results of the second training experiment. The graph illustrates the robot's calculated behavior fitness for each physical context based on the positive feedback gathered from users in the human-robot interactions for each behavior in the two training contexts. There is a significant ($p<.05$) difference in the distribution of votes for the two physical contexts when the robot asked the users to choose the most fitting of the two displayed behaviors. The found most fitting behavior for the largest (6x5m) context was the behavior with intensity level 2 (with positive feedback in 73% of times tested), while the lowest-rated behavior from the same context was the behavior with intensity level 0 which was only found most fitting in 20% of the times it was tested. For the smaller physical context (2x3m) the behavior found to be the best fitting was the behavior with intensity 1 with 66.7% positive votes, while the least fitting behavior was the behavior with intensity level 3 27.3% of the positive votes.

Following both training phases, the robot had fully updated its behavior prioritization in accordance with each interaction result. The visualization of top behaviors for each context in the 10x10 context-representation can be seen in Figure 4. The visualization depicts the two main physical context regions and the voted most fitting behavior intensity in each of them with an intensity level of 2 (yellow) for the 6x5m physical context and an intensity level of 1 (light blue) for the 2x3m physical context. The maximum intensity level of 3 is found mainly in the upper right region of the context representation which matches the largest found physical context measurements in Figure 2. Comparing the physical context visualization and the context behavior representation reveals

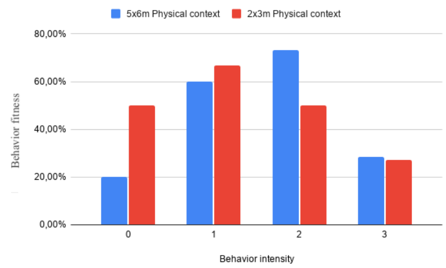

Fig. 3. The calculated fitness of each behavior intensity based on positive ratings for each behavior in the two physical contexts. The blue series depicts the largest (6x5m) physical context, while the red series depicts the smaller (2x3m) physical context. The x-axis shows the different behavior intensity levels while the y-axis shows the calculated fitness of each behavior.

that the adjusted behavior intensity levels intuitively match the physical aspects of each context but also reveals that the measurements performed before each interaction often place the robot between two well-defined context regions in the representation.

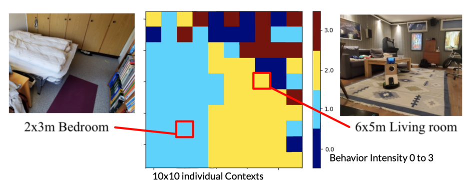

Fig. 4. The context behavior representation. The 10x10 map represents the 100 individual contexts, while each color representing the highest prioritized behavior intensity of each context. The light blue color represents intensity level 1 while yellow color is intensity level 2. The topological positions are similar to those in Figure 2. Note that this map shows the behavior associated with the different contexts, not a map of the physical location.

4.2 Validating the trained framework

The validation experiment included 90 participants. Out of those participants, 58 preferred the behavior identified by the robot as being the optimal behavior for the physical context while 32 participants preferred a different randomly selected behavior instead. A binominal test highlight that it is a significant result with the one-tailed probability of exactly, or greater than, k=58 out of n=90 is p = .004204. There was a slight tendency that the average Likert ratings of the framework-selected behavior were higher than the average ratings of the other three behaviors, but the experiment lacked sufficient participants to provide a significant result to prove that beyond doubt.

Summing up the results there were two main findings. The first finding is that the framework managed to find a sound prioritization for behavior intensity by adjusting the behavior prioritization for each context in accordance with the physical attributes of each context. The second finding is that the trained framework, when put in a never before encountered physical context, managed to identify the best possible behavior for the physical circumstances verified to a significant extent by human observers.

5 Applying the findings

This paper aimed to construct a robot that utilized simple physical context information as a guide to drive its behavior selection. There is a definite and clear relationship between the physical properties of the room and the human-preferred physical properties of the robot's behaviors. The results indicate that as the physical space increases around the robot, and the participants who interact with it, so does the amount of preferred intensity in the robot's behaviors. The robot managed to create regions in its context representation for each physical context and update the same regions with behavior that matched the increased physical dimensions. However, Affecta V3 did not map the context consistently to the same node in the context representation. This stems from the uncertainty of using a single attribute to recognize the current context. Adding further parameters to identify the physical aspects of the contexts would make it more precise. However, there is a strength and a point in using a single attribute, as it is easy to apply to most robots and it provides contextual information even from simples sensors.

The robot prioritized between discrete predefined behaviors using physical context attributes which admittedly is an extreme simplification of complex psychological processes. As it is making assumptions on a sparse set of information it will often be wrong when determining contexts and best behaviors. However, the same can be said for most humans. We don't always find the completely correct behavior for a given situation, we adjust our immediate behaviors and negotiate affective status many times through each interaction [20]. More complex and richer sensors could provide better distinctions between contexts but may also introduce more sensor noise. Some attributes aid behavior selection better than others. E.g the detected color of various rooms would make it easy to recognize a known context, but that attribute says nothing about the optimal behaviors. The kind of behaviors that the robot optimizes for determines the choice of attributes, meaning that it is a tradeoff between high-resolution context distinction and more generalizable behaviors.

The last two behaviors with intensity 0 and 3 were mostly down-prioritized. Outside of them not generally fitting the context, this could also be due to the nature of the interaction. The participants interacted with the robot from a distance between 1-2 meters and a large physical behavior (intensity 3) might seem intimidating coming from a robot, and a lack of movement (intensity 0) might make the robot seem inanimate or uninteresting. However, some people preferred these behaviors and it indicates that personal preference also plays a part in each interaction. The individual mood and personality of each test participant may also influence how each behavior is received.

6 Conclusion

This paper investigated the abilities of a behavior-prioritization framework that adapts behaviors to the physical contexts. The framework enabled a robot to autonomously prioritize between predefined behaviors in each encountered context. The framework was trained in two different physical contexts through 72 interactions with 6 human participants. The ability to distinguish contexts was manually verified as working successfully. The result showed that the robot created distinguishable regions in the visualized context-representation for each visited physical context. The framework also managed to autonomously prioritize behaviors in each identified context. The resulting list of behaviors matching each physical context was learned through interactions with the users, and the calculated fitness of each behavior and the visualized map of behaviors showed that the corresponding behaviors had been correctly prioritized by the robot. The trained framework was verified in an experiment that showed the framework-chosen behavior was the best possible match for a new context as chosen by human observers to a significant extent. The Affecta-context framework highlight the potential in context-based behavior selection and demonstrate the possibility of basing context-based behavior selection on the information retrieved from ad-hoc measurable attributes during an interaction. Future breeds of social robots should adapt to contextual information and this paper arguest that while a richer context distinction may be preferred for context-guided robot behavior selection, even simple attributes can provide the foundation for context informed behavior selection.

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