OBJECT PROPERTIES AND GENERALISATION: DEVELOPMENTAL PSYCHOLOGY TO DEVELOPMENTAL ROBOTICS

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***ABSTRACT*— Having curiosity by nature, humans start to explore surrounding environment at very early age. Such exploration starts by interacting with objects in immediate reach, like toys. Human infants have been observed to make generalisation about their actions on objects and related outcomes by learning from interactions with them. In psychology, it has been found that these generalisations are strongly influenced by objects' visual properties. In this study we present simulation of generalising object properties based on interaction and visual features. The results show that object shape is more reliable than other object visual feature for generalising outcome.**

Keywords: artificial intelligence, developmental robotics, behavioural learning, schema system

1. INTRODUCTION

Humans have curiosity of understanding the world, even universe, by nature. Curiosity is found in most living species, however, humans, being capable of reasoning and developing the knowledge, are involved most to explore and satisfy their curiosity. Humans start to explore the world at very beginning of the life, early infancy, even when they have poor sensory and motor capabilities [1].

Visual experiences are very important to learn about the objects, along with the manual explorations. In fact, visual ability helps to learn motor capabilities and without visual ability infants have been found with delayed motor developments [2-4]. Piaget, in his famous theory of cognitive development, had represented human age into six different learning stages [5]. The very first stage starts from right after the birth up-to two years of age. He labelled this stage as “Sensorimotor” stage, because he believed that at this stage infants' leaning and knowledge is associated with their sensorimotor experiences with the surrounding environment and objects. His theory suggests that object exploration, visually and manually, helps infant to understand about the object physics, its properties and affordability. Infants remember actions on objects, and related outcomes, and have been observed to use those actions on the other, novel, objects to obtain identical outcome [6-8]. However, they extend their expectation to novel objects which have similar visual features to the one/those they experienced before.

Extending expectations or actions/situations to novel objects having particular set of similarities with the objects/situations experienced in previous time can be labelled as “Generalisation”. Shepard believes that human as well as non-humans species posses this generalising capability [9], which helps to learn and extend the learning. In generalising object, objects features, form (e.g. shape, size) & surface (e.g. colour, texture) features, are very important.

Understanding about object properties in early age using visual and manual experiences have been widely studied in the developmental psychology. In those studies, psychologists have found that infants rely on object's form features, rather than the surface features, to generalise and extend actions, and expectations, to novel objects [6-8, 10]. In particular, they rely on object shape for making general conclusions and expect that object of similar shape will give same outcome or show similar behaviour when acted upon them.

Infants have been found to associate and generalise non-obvious properties, such as squashy sound, with objects. Baldwin et al. found that 9-16 months old extend their experience to novel objects which have similar shape to one they experienced before. They presented an object to infants which produced some noise while grasping. Infants were allowed to interact with such object only for 20 seconds and later they were presented similar and different shaped objects, some of them possessed same non-obvious property (squashy noise). In these experiments infants have been found to explore, manually, more those objects which have shape similarity but did not produced the sound as they experienced before. The objects of different shape were explored less, irrespective of having non-obvious property. More manual exploration was observed in surprise state as infants expected the object to produce noise and failure to produce such outcome they tried to explore more.

From above experiment, it seems that infants; 1) generalise very quickly, even with one and 20 seconds experience. 2) Rely on shape for generalisation. Graham & Poulin [7] and Welder & Graham [8] found very similar results in similar experiments, and same two points (generalising quickly and reliance on shape for generalising) are evident from their experimental results.

In practical robotics, robots may need to observe and act upon different objects. These actions, on objects, can be similar in term of kinematics or outcome. For an efficient robotics application, a robot or robotic system should learn from as less experiences as possible and extend the learning to new and novel situations/objects, irrespective of learning environment. This can be possible if robot is able to generalise objects/situations based on the sensory features, especially visual features, as humans do. Various robotist have been working on this topic and we can see some fascinating results as well.

In this paper we are proposing an mechanism for generalising non-obvious object properties related to the visual properties using an adaptive learning tool, Dev-PSchema, for artificial agents. We will evaluate our mechanism using very similar experiment about generalising object properties, performed by Baldwin [6], but in a simulated robotic environment. In section-2 we will discuss about the robotics studies on this topic. In section-3 we will discuss about the tool PSchema and its extended version Dev-PSchema. In section-4, experiment and related results will be discussed. In section-5 well will look into the developmental psychology to validate the results and in section-6 we will end with the conclusions and future work.

2. RELATED STUDIES

Achieving human like intelligence in artificial agents is aim of the researchers in the field of Artificial Intelligence (AI). Researchers, in AI, are working different aspects of learning. Here we are interested in object learning leaning and particularly generalisation. Sinopov & Stoytchev in [11] presented a mechanism for learning and generalising tool use. Learning in this system was performed by the demonstration and using visual features system generalises the outcome of the tool with particular actions. They used compact decision tree model for generalisation and evaluated the system by extending the learning to novel (never experienced before) tools. This system shows good accuracy for predicting outcome for familiarized (experienced before) tools but achieved accuracy 56% in predicting the outcome for novel tools.

Similarly Pastor et. al. developed another learning mechanism for generalising “Grasp-Move-Place” task [12]. This system was trained to perform this task by demonstration. Motion libraries were developed while performing the task by human demonstrator wearing exo-skeleton robotic arm. The motion libraries were then transferred into 7 Degree of Freedom (DoF) robotic arm and system was evaluated by performing same task on novel objects. The position for placing the grasped object was generalised by the system and was able to successfully perform the task. A very similar study was performed in [13]. In this study, researchers demonstrated the generalising capability of the system for reach and transport task. Task was generalised after three demonstrations by finding the common elements in the topological sequence of the action for the given task.

These learning systems, described above, show a good degree of accuracy for generalisation. However, in these studies systems were trained to perform these tasks either by demonstrations [12, 13] or supervised learning [11]. In the field of developmental robotics, it is aimed to develop learning mechanisms inspired from the developmental psychology. In developmental psychology, it is considered that early object learning and actions associated with those are related by sensorimotor experiences [5]. Robotists are also developing system having learning mechanism based on senosrimotor experiences.

Geib et. al. [14] proposed a high level learning mechanism named as Objec-Action-Complexes (OACs). Proposed system is able to learn from the high level sensorimotor experiences and plan actions according to learning experiences. System uses high level representation and authors claimed that system is able to bridge the gap between low level robotic control and high level representation and action planning system. The OACs are learning outcome containing high level sensory states before and after the action and action itself. System uses multiple OACs to find the common elements between them for generalisation. The generalised OACs are referred as Instantiated State Transition Fragment (ISTF), which are used for action planning and prediction. Kruger et. al. [15] implemented this system in their work. Action prediction has been demonstrated in this work using ISTFs, however, system was trained for prediction using supervised learning mechanism in neural networks.

Hermans et. al. demonstrated affordance prediction model in [27]. The prediction model is based on visual attributes of the objects, such as size, shape etc, and physical attributes (e.g. weight) perceived through visual information. This model was trained with Support Vector Machine (SVM) and K-Nearest Neighbour (k-NN) networks to predict the affordances for the novel objects. The prediction for novel objects can be considered as generalisation of attributes for affordance.

Recently, Aguilar proposed another high level learning system for artificial agents termed as "Dev-ER" [16]. This system also uses high level knowledge representation of world and actions. Learning outcomes are in shape sensor motor schemas, containing context and actions. System is also able to create generalised schemas based on the experiences. Generalisation in this system is based on the deductive inference, by creating very abstract to content specific schema. Moreover, in the study, this system was provided with basic action schemas to act in the environment.

The robotic models discussed above, have shown significant results in this area of research. However these models, except [16], are trained with neural networks for learning predictions and generalisations. Model presented in [16] uses deductive inference for generalisation, by creating very generalise learning and develop it to specific learning with experiences. In our proposed mechanism inductive generalisation is used. By which non-generalised learning (schemas) are created initially, which are used create generalised learning with experiences.

3. METHODOLOGY

Piaget believed that human knowledge is stored in shape schemas in the memory and at first stage these schemas are sensor motor experiences only [5]. Further, he believed that infants reason the situations in the world using schemas. This process is referred as "Assimilation". If infant's knowledge is unable to deal with the situations in the world, he/she created new schema accordingly and process is referred as "Accommodation".

Although, Piaget's work has been argued by many psychologists, especially Spelke's core knowledge concept [17], yet it is considered an influential study of infant psychology. AI researchers, also, have developed and implemented learning systems for artificial agents based on the sensorimotor experiences. To the best of our knowledge Drescher [18] was the first one who proposed schema based learning system for artificial agents. He referred such systems as schema mechanism, where learning involved with experiences.

In this work we are using an extended version of adaptive learning tool, PSchema [19], which offers continual, online learning. Inspired from the Piaget's sensorimotor stage of learning from Cognitive theory and Drescher's [18] proposed system, this tool uses sensorimotor experiences for building knowledge and learning are presented in the shape of schemas containing action and context. Fig. 1 shows a simple action schema.

Grasp Schema		
Preconditions	**Action**	**Postconditions**
Colour 'Red/Green' at 2,1 Shape 'Cube' at 2, 1 Touching at 2, 1	Grasp	Colour 'Red/Green' at 2, 1 Shape 'Cube at 2, 1 Sound Observation

Fig. 1: A simple action (grasp) schema

Action schemas contain sensory states before and after actions, known as preconditions and post conditions. System uses excitation calculator to select a schema, based on the similarity with current state and novelty, for execution. Schema building mechanism decides and builds schemas after execution, using “Assimilation & Accommodation” process. We extended this system and named as “Dev-PSchema”. In sections 3.1 we will discuss about the extensions that we made in the system.

3.1 DEV-PSCHEMA

We extended schema building and generalisation mechanisms. In schema building mechanism of PSchema, we extended the system to undergo the accommodation process and create new schema when system get new state or subset of the post-conditions of executed schema. In original version of “PSchema” system did not created new schema when outcome of an action schema was subset of post-conditions of any of the stored schemas, having the same actions and preconditions. Schema building routine is called every time sensory state is updated in the system, usually before and after execution of an action. The extended schema building mechanism is described in simple form in Algorithm 1.

***Algorithm 1*: Updating State & Create Schema**
Procedure Update_state(State New)

if *Last schema* **OR** *Last state is Null* **then**
Return
end if
if *New state different from Last state* **then**
Preconditions = Last state
Action = Last schema action
Postconditions = New state
make new schema(Preconditions; Action; Postconditions)
end if
if *New schema not in memory* **then**
Add New schema in memory
Generalise(New schema)
end if
Return
end procedure
end

Schema, for action execution, is selected using excitation calculator which finds the similarity between the sensory state in the environment and schemas in memory. Here, most salient schema (post-conditions matching with new state) is selected for execution. Here we are using same algorithm for excitation as it is in PSchema. Algorithm for excitation calculator can be found in [20].

We extended generalisation algorithm as well. Generalisation in PSchema was decided on number of schemas that have similar action and context (preconditions and post-conditions). If a property appears in different values in similar schemas then that property will be generalised, replaced with dollar sign “$” including a random, unique alphabetic character. With “$” sign system indicates that property is generalised, whereas alphabetic character represent any value of that property. Generalisation algorithm in PSchema can be obtained from [20]. A simple generalised schema is shown in Fig. 2.

Complete Generalised Schema		
Preconditions	**Action**	**Postconditions**
Colour '$a' at $b, $c Shape '$x' at $b, $c Touching object	Grasp	Colour '$a' at $b, $c Shape '$x' at $b, $c Holding object

Fig. 2: A simple generalised grasp schema

Fig. 2 shows that properties, such as object colour, shape and position, are generalised. This generalise schema can be used to grasp any object (if graspable) when end affecter is touching the object and will result in holding the object.

In Dev-PSchema, we made changes in generalisation algorithm and now systems generalises those properties, as well, which appeared in bootstrap schema (see IV-B.1). These changes enable the system to identify the properties which appeared in result of action and reaming will be generalised even if they appeared once in similar schemas. Simplified, extended algorithm for generalisation is shown in Algorithm 2.

Algorithm 2: **Generalisation Algorithm**

Procedure GENERALISE *(New Schema; Schema Memory)*

if *New don't have preconditions* **then**

return

end if

for *each schema S in Memory* **do**

if *S not generalised AND have similar context* as *New* **then**

Add \S" in List similars

end if

if *action in S and New are similar AND postconditions in S are less than postconditions in New* **then**

Add postcondition properties in old props

end if

end for

trial schema = copy of new

for *each property* ***P*** *and* ***P2*** *in precondition and postconditions respectively of schema*

S from List similars **do**

if *Value of* **P** *and* **P2** *is same OR* **P** *in old props* **then**

Replace value of each property P in trial schema with random unique alphabet

end if

end for

add trial schema in memory

end procedure

end

This mechanism will help to learn the system about the dependencies for an schema and the common properties in the schema will be generalised. In the work we get two types of generalised schemas. In one type all the properties are generalised, named as complete generalised schema. In other type, named as partial generalised schema, one or more than one property will not but generalised but at least one property will be generalised.

4. EXPERIMENT AND RESULTS

To evaluate the system we will perform experiments and observe generalised schemas. We expect that system will create complete generalised schema when it finds dependent properties with different values and partial generalised schema when dependent property is only available in one value. Here we considered object shape as dependent property for a particular grasp schema. If system finds similar schemas in memory with different types of shape then it will generalise the shape, else it will give partial or non generalised schemas, depending upon the state.

4.1 EXPERIMENTAL SET-UP

We used a simple simulator to evaluate the system. Simulator contains end effector, a hand, to perform actions in the environment. Simulator is able to perform two basic actions, reach and grasp. These actions are defined at high level, without low level kinematics of the agent, robot. Simulator also contains objects of different shape and colour. Objects are defined with their high level sensory information, colour, shape and position. In this experiment we are using two types of objects. One, which provides some non obvious property e.g. sound, when grasped. Spheres and cubes are of this category, irrespective of their colour. Cylinders, irrespective of colour, are objects of the second category which does not produce any non-obvious property when grasped. Fig. 3 shows the environment of the simulator.

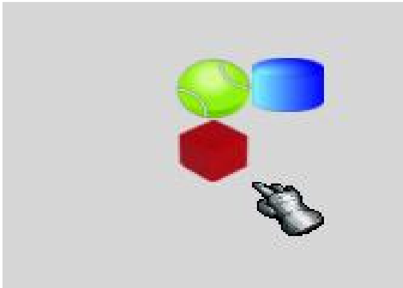

Fig. 3: Simulator environment

4.2 EXPERIMENTAL STAGES AND RESULTS

Experiment is started with the "Boot strapping" process. After this, first object is introduced to interact with. To evaluate the system, we divided further experiment into four different paths(A-D), where object of same/different shape and colour, with respect to first object, are introduced. All of the objects at this stage are of same category as first object which produced sound when grasped. At later stage an object of different category, cylinder, is presented at each path. Fig. 4 shows the experimental flow diagram.

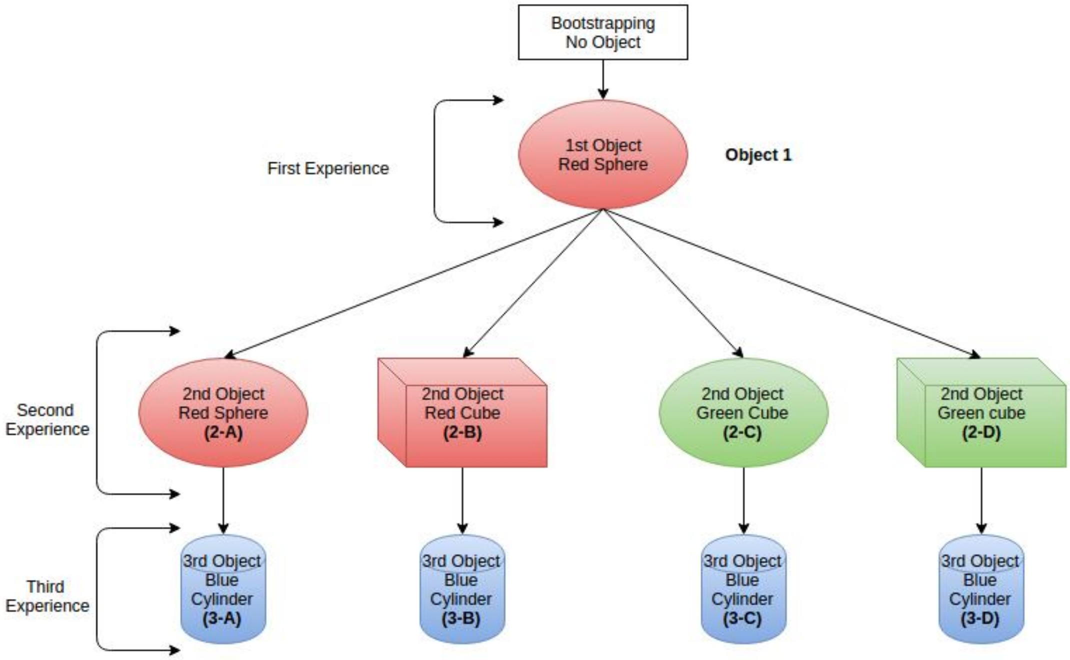

Fig. 4: Experimental stages

It should be noted that object is represented with separate colour and shape observations, considering as separate sensory channels. Each of the stage mentioned in the Fig. 4 is discussed bellow.

1) Bootstrapping: At this stage system is allowed to perform all the basic actions. In this case reach and grasp. Simulated end effecter, Hand, will reach at each space a finally grasp action in the environment and store schema for the action. We refer these schemas as bootstrap schemas, which generated without any object in the environment. These schemas do not have preconditions. It should be noted that grasp action without any object in the environment will result in hand close, which give touch simulation generated by touching own hand. Fig. 5 shows reach and grasp bootstrap schemas.

Reach Schema		
Preconditions	**Action**	**Postconditions**
	Reach	Colour 'Hand' at 1, 1

Grasp Schema		
Preconditions	**Action**	**Postconditions**
	Grasp	Colour 'Hand' at 1, 1 Touching object at 1, 1

Fig. 5: Experimental Stages

This process provides the basic set of schema for basic actions. Which will be used to interact with objects and higher level of action schemas will be created.

2) First Experience: At this stage object is introduced in the environment. First introduced object is red sphere, which produces sound when grasped. Introducing an object, in the environment at any reachable position, triggers the reach schema for that position by calling memory of own hand at that position. When object reaches that position, it touches the object, which results simulated touch sense. This touch sense excites the grasp schemas, as it is the only schema that contains the touch sense. System executes the grasp schema and object produces sound. This new observation, sound, triggers the system undergo schema building process and creates new schema. Fig. 6 shows the step by step process at this stage. After system completes the schema building process, object is removed from the environment and moved to next stage.

3) Second Experience: At this stage, four different learning paths are produced by introducing different objects of same category but at different positions. The change in object shape, colour or position triggered the system novelty and system

interacts with the object. This stage resembles the four different individual babies at same learning age, having same experience of first object.

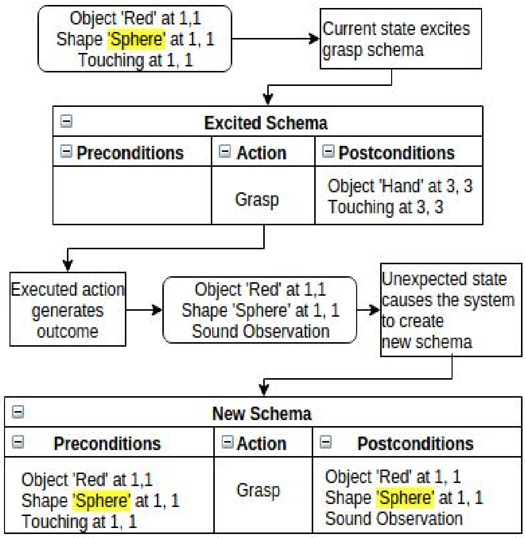

Fig. 6: First object experience

Reach and grasp schemas are selected and executed, respectively, at all four paths when object is introduced. At path A and C where object of same shape but same and different colour from the one experience before, are introduced. After creating new grasp schema, for either of these objects, system undergoes through generalisation process as two schemas with same action and similar context are present in memory. Schema building process for paths 2A or 2C is shown in Fig. 7.

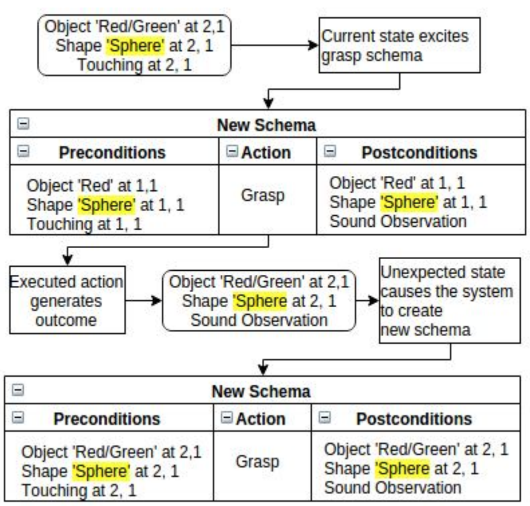

Fig. 7: Second object, same shape same/different colour

Similarly for paths 2B and 2D system undergoes the same process as shown Fig. 7, except objects are of different shape. At every path at this stage system undergoes for generalisation process and creates generalised schemas. For paths 2A and 2C system creates partial generalised schema and for 2B and 2D system creates complete generalised schemas. Both of these schemas are shown in Fig. 8.

Partial Generalised Schema		
Preconditions	**Action**	**Postconditions**
Object '$a' at $b, $c Shape 'Sphere' at $b, $c Touching at $b, $c	Grasp	Object '$a' at $b, $c Shape 'Sphere' at $b, $c Sound Observation

Complete Generalised Schema		
Preconditions	**Action**	**Postconditions**
Object '$a' at $b, $c Shape '$x' at $b, $c Touching at $b, $c	Grasp	Object '$a' at $b, $c Shape '$x' at $b, $c Sound Observation

Fig. 8: Partial (top) & complete (bottom) generalised schemas

From Fig. 8 it is clear that system creates partial generalised schema, not generalising shape, when object of same shape with same/different colour is grasped. For object having different shape, system creates complete generalised schema, generalising shape, colour and position.

4) Third Experience: To evaluate the changes we made in schema building, we introduced another object of different category. This object, cylinder, when grasped produces no sound, unlike the last two object experiences. Introducing this object in the environment triggers the system to use generalised grasp schema to grasp this object. From the post conditions of the schema, system expects that this object will also respond with sound when grasped. However, failure to get such observation, system undergoes the “Accommodation” and create schema for this object.

This new schema confirms the two processes; 1) System is able to deal with over- generalisation. 2) System creates new schema even outcome is subset of the schema post conditions. The results produced in this experiment are further discussed in the section 5.

5. DISCUSSION

We started our experiment with bootstrapping process, where system builds basic set of schemas. It can be argued that system learns about these actions in supervisory learning mechanism. However, the system performs random motor actions in unsupervised environment and without any object present to interact with. This resembles to the motor babbling in infants. Where infants learn about own movements and control them while observing and acting randomly [5]. Goldstein also believes that humans learn own motion observing changes in environment and linking proprioceptive information with it [21].

From the results of the second experience of the object, we obtained partial generalised schema for object having same shape and complete generalised schema for objects of different shape. This output is similar to experimental results has been reported in [6, 8]. In their experiment researchers found that infants expected same non-obvious property from the object of same shape, from the one they experienced earlier. These results shows that colour of the object have no effect on this. Object having same shape, irrespective of colour, were expected to posses the non-obvious property. However, objects of different shapes, even same colour, were not considered as same and non-obvious property was not expected.

In various other experiments it has been found that infants rely on shape, rather than the colour, to recognise and identify the object [7, 22-25]. These evidences from the psychology show that shape is more important feature than colour when it is associated with certain situations or conditions. So the question arises why shape of the object is more important than the colour? Psychologists have different theories on this matter. Researchers in [7] believe that shape feature is easily perceivable, which does not require more experiences for recognition. They also believe that shape is an integral part of the representation used for objects. However, Nicholson & Keith [23] argues that colour information is also used in representation but shape information is more influential. They believe colour information speeds up the recognition process but, yet, shape is most reliable information and both are encoded separately in representation. Similarly Wilcox [25] believes that infants link shape information with the event outcome, hence they use same information to perform predictions.

These evidences clearly supports that shape is more important in object representation and it is separately represented from colour. This validates our object representation, separately in colour and shape. Our findings are also in-line with these evidences as we obtained partial generalised schemas for same shape objects but complete generalised for different shapes. The generalised schemas represent a concept that schema systems builds with experiences. At stage 2A or 2C system builds concept that spherical object of any colour will produce sound when grasped. Similarly for stages 2B or 2D it builds the concept that object of any shape and colour will produce sound when grasped. These concepts are in the shape partial and complete generalised schemas respectively.

At stage 3A-D, system experience third object and creates new schema. System initially uses its concept to deal with this new object. For stage 3A or 3C system believes that only spherical object will produce the sound, which is verified. However, system doesn't have experience with new object it undergoes schema building process. Similarly, at stage 3B or 3D system expects that new object will produce sound when grasped. But failure triggers the system to create a new memory, schema, about this experience.

At third stage system creates new schema, no matter at which path it is (A-D). The information, no sound, while grasping ends up with new schema. This what expected from infants as well when they fail to deal new information with their existing knowledge. Piaget [5] believes that using "Accommodation", human builds up new knowledge when failed to deal using existing. In one of recent study, Stahl and Feigenson found that infants' learning is affected by the expectation of their actions and related outcomes [26]. Their findings support Piaget's thought about "Accommodation" process in learning.

6. CONCLUSION

Considering human learning model, in developmental robotics it is aimed that a learning model should be continuous, adaptive, domain independent and extending learning in novel environment. This learning model has ability to learn continuously and use the past learning in novel situations. Learning bootstrap schema and using those in novel situation when objects were introduced, shows the capability of the system for continuous, adaptive learning, irrespective of the environment. System is also able to build hierarchical structure of knowledge, as it uses bootstrap schema for actions on the objects and develops next level of knowledge for those actions by creating new schemas.

Generalising capability helps the system to learn and build concepts. These concepts may not fit every situation, however this is what have been observed in humans as well, where humans generalise very quickly and then learn from their mistakes. Experiment in this study demonstrated that system makes generalisations which may fails, as in case of 3B and 3D. Failure generalisation triggered system to explore further and develop new knowledge.

We believe this system provides a way to investigate the learning capability in early infancy in humans by incorporating representation of knowledge at that age. This system works with high level representation and abstract actions. Thus system need to work with low level sensory information processing such as visual libraries and low level kinematics system of an artificial agent for abstract actions. In future we are looking to extend this mechanism for considering failure in more specified way and develop different levels of generalisations. We will also like to integrate this system with a robotic platform in near future.

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