An Approach for Modeling Grasping Configuration Using Ontology-based Taxonomy

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***Abstract*— The handling of flexible materials is complicated task in robotics and automation. Due to deformability and fragility of flexible materials, robots are equipped with the state-of-the-art sensors and grippers to perform such tasks. Nonetheless, industry still lacks for approaches and techniques for handling these materials. Therefore, several industries and mass production systems require hiring human to perform the deformable materials-related task. These tasks might include usage of toxic martials (e.g. carbon fiber sheets) or dangerous tools (e.g. sharp cutting knives). In this regard, this paper presents an approach for selecting grasping configuration of objects based on the product's properties such as rigidity, surface roughness and shape, and the required task. Briefly, this research is based on several published taxonomies for modeling the hand of the human while grasping different objects. After refining the taxonomy, an ontology model is populated which will be queried for specifying the gripper's properties such as number of fingers and required grasping force that can perform the selected task on the selected product. Finally, this research presented a use case form the REMODEL (Robotic tEchnologies for the Manipulation of cOmplex DeformablE Linear objects) project in order to assess and validate the approach. For the future, this research expected to include the selection of the grippers, the robotic arm and its approach for grasping the product.**

Keywords— Robotics and automation, Grasping, deformable materials, Knowledge based systems, Cyber-physical Systems

I. INTRODUCTION

The concept of Cyber-physical Systems (CPS) merges the reality of physical systems, e.g. velocity of pump or temperature of a furnace, and the virtuality of data, information and computer applications to optimally control and monitor the physical systems [1]. Thanks to the advances in Information and Communication Technologies (ICT), CPS are evolving and reaching maturity that permit their usage in some critical and sensitive systems. As an example, the application of self-driving vehicles requires precise modeling and understanding the physical world, optimization in decision making and critically applying the control signals to avoid accidents or sudden changes. Moreover, and as another example, robotics is considered to be CPS where the physical robot is controlled by an application that uses sensors' data to control and manipulate the physical system. considered to be critical applications, medical operations or fragile material handling which requires precise and critical time response to avoid any accident.

Flexible materials are complicated to be handled by robots as well. Due to their dynamic changes in shape and dimensions, flexible materials require special grasping and handling measures. As an example, a material can be fragile and deformable like paper sheets or delicate sea food. These materials require specially designed and modified grippers to be handled during the production. In addition, the design of the robot motion requires considering the behavior and material properties of the handled product.

This paper aims to present an approach for selecting the proper grasping configuration, based on the product that expected to be handled and the task which requires handling the product. The selection engine is based on ontological-based system which is populated with human modelling for grasping objects. This research has been initiated following the initiation of the REMODEL (Robotic tEchnologies for the Manipulation of cOmplex DeformablE Linear objects) project which is funded by the European Commission [2]. This project targets the handling of Deformable Linear Objects (DLOs), which includes cables, wires, harnesses and hoses. Once the grasping configuration is identified, the selection of grippers, robots and gripping approach can be designed. However, the scope of this paper is recognition of the grasping configuration only.

The rest of the document is structured as follows: Section II presents the related research and state of the art in the field of Robotics and manipulation and Grasping and Human grasping modelling. Section III presents the approach of this research. Section IV provides the implementation of the presented approach. Finally, Section V concludes the paper and provides possible future work.

II. THEORETICAL BACKGROUND AND RELATED WORK

A. Robotics and Manipulations

Contemporary industrial robots are crucial components for automating various processes involving material handling, assembling, disassembling, welding, dispensing, etc. The similarity of the robot's functionality to humans and the improved performance efficiency and accuracy of repetitive tasks have caused their usage to grow exponentially in recent years. Singh et al. compare their similarity and discussed the reasons which make them the preferred choice for industries of all scales [3].

The robots of today, produced by the major manufacturers, fall under the defined abilities and characteristics made for CPS, as was categorized by Mikusz and Csiszar [4]. They delve deeper into avenues where the robots behave like a CPS, but the perspective of Industrial robots as CPS in the sense of opened and linked up systems (in contrast to embedded systems), is of more relevance in this discussion. This essentially deal with the protocols available for the robot to interface with the external environment, which is predominantly through the use of sensors. Mikusz and Csiszar primarily focus on analyzing the usage of sensor data to predict uncertainties and improve the smartness of the robot operation, conforming to the theories of CPS detailed by Geisberger and Broy [5].

Correspondingly, similar protocols could be utilized to teach the robot, to perform its tasks. The traditional methods of programming robots used in majority of the industrial applications are online programming, using a teach pendant and offline programming, using the CAD based simulation environment, as evidenced by Rossano et al. [6] and, Ahrens and Pageau [7]. However, these do not highlight the features of the robot which makes it a CPS. Additionally, they lack intuition and require a skilled operator/ programmer who has experience in handling the proprietary teaching tools. Other techniques such as lead through programming as explained by Sang Choi et al. [8] and Leire et al. [9] capitalize on the developments in sensor technology and provide the user an intuitive and easier alternative to program their robot on-line. Lead through programming involves the user to physically hold and guide the robot manipulator to the desired targets with effective configurations, and also trace the path to be followed by the manipulator. And, teaching by demonstration involves the user to guide the robot (without direct contact), by using a combination of wearable devices with bendable sensors (smart glove) and visual sensors to trace the users hand gestures and position at the system run time.

The usage of intuitive teaching techniques has the benefits of lower costs due to reduced time and programmer cost, reduced reliance on proprietary hardware and software, etc. Additionally, robot trajectories which are too complex to be defined by traditional methods, could be easily programmed by these intuitive teaching methods, as highlighted by Schraft et al. [10]. The incorporation of human driven motions as a form of programming by means of sensory inputs is one of the primary attributes of CPS. The effectiveness and the improved trajectories obtained by emulating human actions is the next important point to consider. The upcoming sections of this document would explore this further, with an emphasis on material handling.

B. Objects Grasping and Human's Hand Modelling

Grasping an object with an arbitrary shape is a very simple task for humans. Human perception and experience make this task so intuitive, like if it didn't require any effort to select the proper grasp for every situation. However, when it comes to robotics, determining the type of grasp that the robot has to perform can be really arduous. According to this, we could describe humans as the perfect robots, hence modelling human behavior, in this case human grasping, can guide the robot on how to act in any situation.

Even if we had a perfect model of human grasping, we still have to face the problem of replicating that behavior on the robot. Nowadays there are many different robotic gripper topologies and technologies, some of them are similar to human hands, whereas in other cases, imitating human grasps is a challenging labor. Samadikhoshkho et al. [11] provided a review on robotic grippers classifications. They classified grippers according to its topology in seven groups: robot grippers with two fingers; robot grippers with three fingers; robot grippers with flexible fingers, mainly used for handling fragile objects; multi-finger and adaptative grippers, that includes robotic hands; grain-filled flexible ball grippers, where the gripper deforms its shape to match the shape of the object; fellow grippers, used to grasp an internal cylindrical surfaces by expanding its shape, and O-ring grippers, used for grasping the inside diameter of O-ring seals. From the actuation point of view, they distinguish among five types of grippers: cable-driven, vacuum, pneumatic, hydraulic and servo-electric. Another interesting classification for robotic grippers is by their application [11], [12], which can help when determining the suitability of a gripper for a specific task.

Revising literature, we can find many approaches for human grasping modelling. In 1946, Slocum and Pratt [13] classified the human grasps into three general types: grasp, pinch and hook. It was in 1956 when Napier [14] introduced for the first time the concept of classifying grasps by their need for precision or power, but this idea wasn't developed until 1962, when Landsmeer [15] made the distinction between "power grip" and "precision grip". Later, in 1971, Skerik et al. [16] introduced also a third category, the intermediate grip, a concept that was later included by many authors like Kamakura et al. [17] in 1980. In 1982, Kapandji [18] created a taxonomy including 21 different grasp types, defined in a hierarchical way. Seven years later, Cutkosky [19] constructed another hierarchical taxonomy that could distinguish among 15 grasps according to the task requirements and the shape of the object. This was a very interesting taxonomy by that time and nowadays this taxonomy is still been extensively used in robotics, however Cutkosky didn't consider the mechanical properties of the objects for this classification. In 1992, Kang and Ikeuchi [20] developed a very innovative taxonomy based on the 'contact web', which was defined by them as "a 3D graphical structure connecting effective points of contact between the hand and the grasped object", which provides a more continuous classification of grasps. Two years later, in 1994, Mackenzie and Iberall [21] introduced also in his taxonomy an "opposition space classification", where they distinguished between three opposition types (pad, palmar and side opposition) and they also considered the number of virtual fingers (VF). Each group of fingers that work together as a functional unit compose a VF.

Already in the 2000s, we can find some good taxonomies, that took the knowledge from the previous approaches and expanded it. In 2013, Bullock et al. [22] created a high-level taxonomy of movements of the human hand for manipulating objects. This taxonomy also included no contact movements and non-prehensile grasps. Finally, our literature review finishes in 2016, when Feix et al. [23] created one of the most complete human grasping taxonomies that we have nowadays. They analyzed and compared 22 existing human grasp taxonomies and synthesize them into a new one, called "The GRASP Taxonomy".

The GRASP Taxonomy considers only one hand grasps in which the object is not in relative movement with the hand and where the grasp doesn't depend on gravity, so if a person turns the hand, the object won't fall. They used a matrix arrangement for classifying the grasps. Columns have three levels for differentiating grasps. The first level divide grasps according to its power/precision requirements, the next finer differentiation considers the opposition type, that also defines the VF 1, and finally the third level classifies the grasps by the number of virtual fingers involved. Rows just make a distinction by the position of the thumb. Just considering the already mentioned divisions they could differentiate 17 different grasps, however if the size and shape of the object is also considered, the taxonomy can be extended up to 33 different grasps. Some of these grasps are shown in Fig 1.

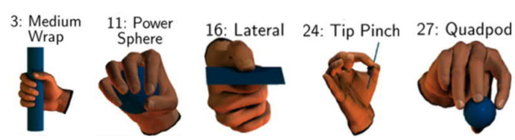

Fig 1. Five samples of the 33 different human grasps types distinguished in [23].

III. CPS FOR MODELING PRODUCT-BASED GRASPING

A. The Refined Grasping Taxonomi

After analyzing the evolution of human grasping modelling during the last 70 years, we could observe that great advances have been made in this field, achieving very complete taxonomies that can differentiate a large number of human grasps. However, most of these taxonomies are focused mainly on the configuration of the hand when grasping, but not in the situation that has created the need for that grasp. The aim of human grasping modelling for robotics is not to imitate the human grasp, the objective is to understand the relationship between task requirements and the grasping "solution" adopted to meet those requirements [19]. Based on this information the robot will select the proper robotic grasp for each situation. In order to obtain this knowledge, we have to relate the object (defined by its shape and mechanical properties) and the task that we are going to perform with it, with the different human grasp types.

In this paper, a taxonomy that provides the different human grasp possibilities for each situation (considering a situation as the combination of the object to grasp and the task to perform) is presented. For this taxonomy a simplified version of the grasp types distinguished in [23] is used, as this is probably the most complete classification of human grasping that we have nowadays. We grouped some of these grasps, that were almost functionally identical, reducing the list from 33 to 25 different grasp types.

We chose a matrix arrangement for representing this new taxonomy. Rows are arranged according to the mechanical properties of the object and they have four levels, considering the weight (heavyweight, middleweight or lightweight), the size (big or small), the surface finish (smooth or rough) and the rigidity (rigid or deformable) of the object, from outer to inner, so that all the combinations are considered. We selected these four properties because they are the ones that influence the most in the selection of the grasp type. The values employed for them are just descriptive, no threshold values are given to distinguish between, for instance, smooth or rough objects. This is because the idea of this taxonomy is to set a starting point for future researches, where these concepts will be further analyzed, adjusting the numerical values to be the most representative possible of reality.

Columns represent both the task and the shape of the object. A first distinction is made according to the general requirement of power or precision of the task. The next finer differentiation depends on the shape of the object. Only primitive shapes are considered in order to not make the taxonomy very complex, thus the real object to grasp must be treated as a cylinder, sphere, cuboid or cone. Moreover, disk shapes can be treated as flat cylinders and sheet shapes as flat cuboids.

This arrangement contents 192 different combinations and within each of them, all the considered grasp types that can be used for that situation are specified. Additionally, some constrains and specific functionalities are considered within each combination, for instance the grasp types that can deal with hot objects (this can be observed in Fig 2).

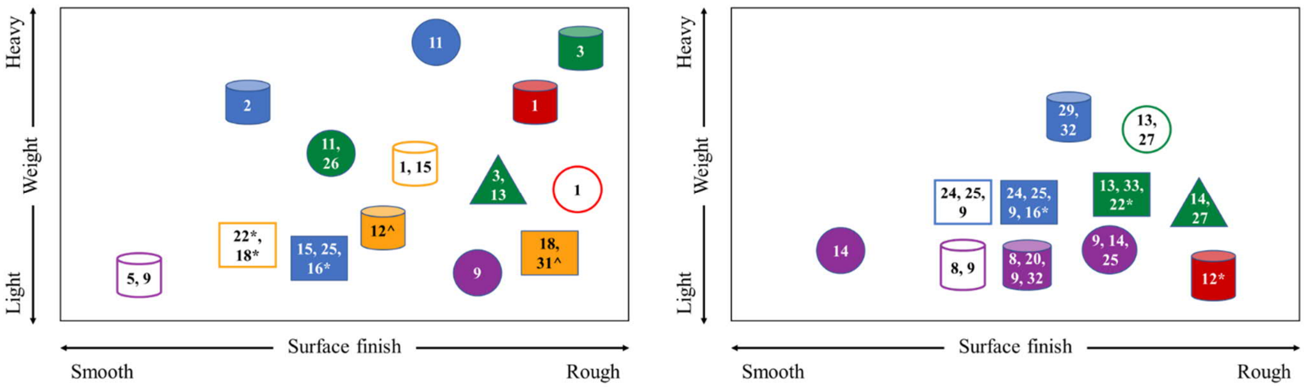

Fig 2.Graphical representation of the grasp taxonomy. The numbers in these graphs correspond to the numbers used by Feix et al. in [23] for identifying each grasp type. The color is used to represent the size of the object: red (very big), orange (big), green (medium size), blue (small) and purple (very small). The shape represents the shape of the objects: cylinder (cylinder), circle (sphere), rectangle (cuboid) and triangle (cone). Regarding to rigidity, rigid objects are filled while deformable objects only have border. Finally, some symbols are used to set constrains: '*' is for flat objects (a disk in case of cylinders and a sheet in case of cuboids) and '^' for hot objects.

Due to the complexity of this taxonomy it is not possible to show a table with all its information, hence some representative samples have been selected and presented in two graphs, for power and precision grasps (see Fig 2). The numbers in these graphs correspond to the numbers used by Feix et al. in [23] for identifying each grasp type. We can observe an unpopulated zone for very heavy smooth objects, mainly for precision tasks. This is because only one-hand grasps are considered for this taxonomy. Another interesting thing than can be detected in the graphs is the presence of clusters (they are easy to see because of the color scale representation used for the object size), which indicates that the taxonomy is coherent. Finally, the differences between smooth and rough, and rigid and deformable objects, are highlighted in the precision graph. We can see that the number of possible grasps is usually reduced when the object is smooth or deformable.

B. *The Ontology Model*

After the selection and categorization of the human hand posture taxonomy, this subsection presents the ontological model for categorizing the grasping configurations based on product and its properties and the task which will be executed on the product. This will allow selection of grippers, robots and the needed configuration of the working space based on the grasping configuration. It is important to mention that this paper focus on the grasping configuration selection.

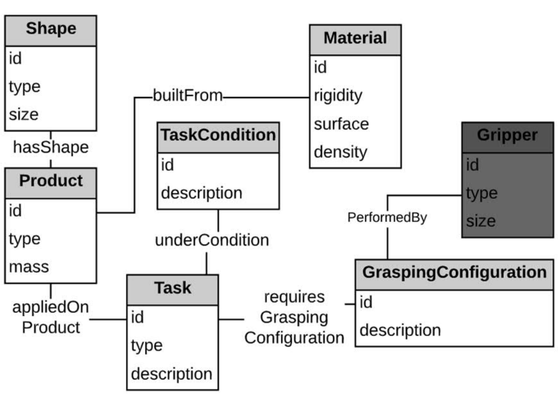

Fig 3. PTG (Product-Task-GraspingConfiguration) ontology model

The PTG (Product-Task-GraspingConfiguration) ontology model is shown in Fig 3. The Product class includes the mass as identifier of the weight of the product. Then, the product is associated with Material class via builtFrom object property to link the rigidity and surface of the product. Meanwhile, the Shape class is associated with the product via object property hasShape. This link provides the identification of the shape of the product. After that, the Product class is associated with the Task class by appliedOnProduct object property. This links the products with the task. Additionally, the Task class is associated with the TaskCondition class. In this regard, the TaskCondition class includes a description data property which presents the special case of the task. As an example, and as described in III.A, some of the categorized tasks include special conditions that affect the grasping configuration such as handling hot objects. Finally, this Task class is related with the GraspingConfiguration class via requiresGrapingConfiguration object property, which contents the numbers of the human grasp types specified in [23], as well as several properties of each grasp configuration. Additionally, the selection of the gripper could be made by associating the Gripper and the GraspingConfiguration classes via performedBy object property, but this is out of the scope of this paper and will be investigated in future research.

C. *General Architecture*

The designed architecture follows the paradigm of the CPS concept by controlling the physical systems (i.e. robotic arm manipulation and gripper selection) and the executed operation via applications based on the outcome of the ontology systems. On one hand, the Manufacturing Execution System (MES) will sort the tasks based on scheduling and production optimizations algorithms. These tasks are stacked in order to be executed. As shown in Fig 4, the envisioned system will support the robot in order to grasp objects based on the task and the product properties. For the focus of this paper, the knowledge engine will provide only grasping configuration. The required gripper and the approach for grasping the object will depend on the object and the required task. As an example, picking a bottle and then pouring the liquid requires approaching the bottle from the side to avoid blocking the tip of the bottle.

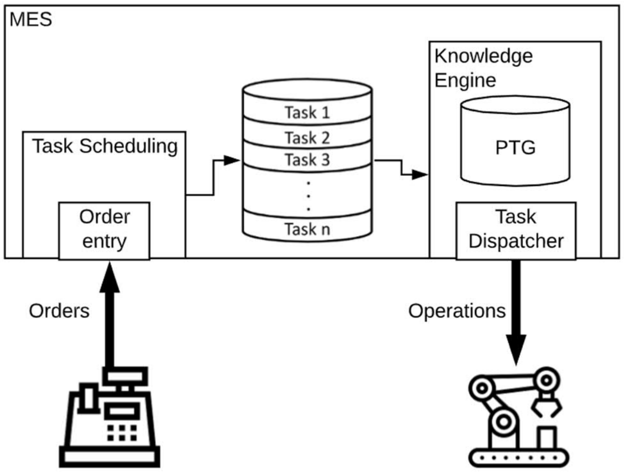

Fig 4. System high level architecture

IV. IMPLEMENTATION

A. The REMODEL Use Case

The Factories of the Future would experience a further increase in the implementation of robotic manipulation for an increasing range of applications, which are currently too complex and intricate to automate. The surge in the development of robotic systems, which are capable of autonomously handling tasks, independent of their material properties, size, shape and behavior, is bringing about a change in worker welfare and socio-economic dynamics. The project REMODEL of the H2020 funding program, is one such research consortium, which is currently working towards implementing existing hardware and software technologies to manipulate complex Deformable Linear Objects (DLOs). This involves handling and routing DLOs for several use case scenarios, taking into account their complex behavior, and concurrently integrating this knowledge with proper manipulation and perception skills, provided by vision and tactile sensing systems. A bimanual robot is utilized as the physical actuator for performing the operations, based on the inputs from the previous systems in real-time.

This paper presents a practical example of the application of the aforementioned grasp taxonomy and ontology model for determining the proper human grasp types in a particular use case of this project, which deals with wire harness assembly for the automotive sector. In this use case, several wiring harnesses are assembled using a platform that includes jigs, each of them with guides for arranging the different branches of the wiring harnesses and with spots for taping groups of cables in certain locations. Thus, this assembly process involves various tasks, currently done manually, such as placing connectors or routing cables through certain guides, that require different types of grasps. The human operator performs a plethora of different grasps to handle objects of low to medium mass and size, low surface friction, and varying levels of deformability. All the observed grasps are included and classified in the taxonomy presented in section III.A (an example of them is shown Fig 5). Hence, using the ontology model developed in this paper, we can check if the grasp types that it suggests match with the grasps performed by the operator, which would indicate how is the efficiency of the model for predicting the human behavior.

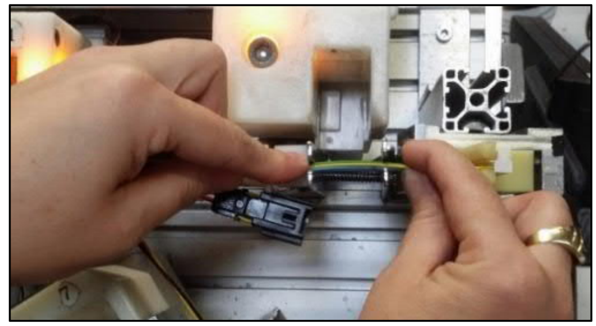

Fig 5. A worker assembling the harness, picking the cable with the Right hand using the Palmar Pinch (9) grasp and routes the cable with the Left hand using the stick (29) type grasp

Next section goes into detail with the population of the ontology models (with the taxonomy presented in section III.A) and with the selection queries, that return a suggestion of the most appropriate grasp types in a specific situation.

B. Populated PTG Model and the selection queries

Following the description of the use case selected to prove the efficiency of the ontology model, presented in section IV.A, the knowledge base considered will include two tasks; picking and placing a connector and routing a cable (or group of cables). The components handled in both tasks will be categorized as light weight products and small in size. Then, routing a cable includes grasping the cable and inserting it into the required guides. In this task, the grasping occurs on the cable, which has a smooth surface and a cylindrical shape, is deformable and requires precision. This condition can be seen in first row in TABLE 1. Whereas, for picking and placing a connector, the grasped element is the connector and due to the presence of different connectors types, both smooth and rough surfaces can be found. In addition, the connectors are rigid and its shape is modeled as a cuboid. Regarding the task, it is considered to be a 'precision' task, as the applied force could damage the connector and positioning the connector requires some degree of accuracy.

TABLE 1: GRASPING CONFIGURATION OF THE USE CASE

Surface	**Rigidity**	**Shape**	**Grasp types**
Smooth	Deformable	Cylinder	9, 29
Smooth	Deformable	Cuboid	9, 14, 27
Smooth	Rigid	Cylinder	9, 7, 29
Smooth	Rigid	Cuboid	16*, 9, 14, 27
Rough	Deformable	Cylinder	9, 29
Rough	Deformable	Cuboid	25, 9, 14, 27
Rough	Rigid	Cylinder	9, 7, 20, 23, 29, 32
Rough	Rigid	Cuboid	16*, 25, 9, 14, 27

It is noticeable that the table does not include mass, size and the task requirements. This is because the values of these properties are light, small and precision for all the tasks analyzed in this use case, so only the grasp types classified within these values in the developed taxonomy were considered when populating the ontology model. Finally, the * represents that special condition of having flat object.

After identifying the needed features and the required grasping configurations, the ontology model is populated with the use case description. Firstly, three materials have been added to the model which include plastic and rubber. The plastic represents the connector and since there are different types of connectors, there are two instances of plastic material, one allows more slipping than the other. For shapes, cuboid and cylinder have been added to represent the shape of connector and cable respectively. For the products, five have been added to represent different cables with different thickness, and two connectors as described before. Finally, the different grasping configurations have been added following the refined taxonomy in III.A.

A query has been designed for each task to retrieve the proper grasping configurations. As shown in Fig 6 and Fig 7, the queries consider surface, rigidity and shape as inputs. Then the knowledge engine will provide which are the grasping configurations that satisfy the task and object conditions, as shown in Fig 8.

```
PREFIX ptg: <http://remodel.tau.fi/fast-lab/PTG.owl#>
SELECT ?GraspingConfiguration
WHERE
{
    ?Material ptg:surface "smooth".
    ?Material ptg:rigidity "deformable".
    ?Product ptg:hasShape ptg:cylinder.
    ?Product ptg:builtFrom ?Material.
    ?Task ptg:appliedOnProduct ?Product.
    ?Task ptg:requireGraspingConfiguration
    ?GraspingConfiguration.
}
GROUP BY ?GraspingConfiguration
```

Fig 6. Query for selecting grasping configuration for routing the cables

The query in Fig 6, represents the grasping on the cable as it was described as smooth, deformable and cylindrical. Meanwhile, Fig 7 shows the query for grasping on the connector, which is described as smooth/rough (in this case a smooth one is considered), rigid and cuboid.

```
PREFIX ptg: <http://remodel.tau.fi/fast-lab/PTG.owl#>
SELECT ?GraspingConfiguration
WHERE
{
    ?Material ptg:surface "smooth".
    ?Material ptg:rigidity "rigid".
    ?Product ptg:hasShape ptg:cuboid.
    ?Product ptg:builtFrom ?Material.
    ?Task ptg:appliedOnProduct ?Product.
    ?Task ptg:requireGraspingConfiguration
    ?GraspingConfiguration.
}
GROUP BY ?GraspingConfiguration
```

Fig 7. Query for selecting grasping configuration for picking up cable

The result of these queries is shown in Fig 8. Cable routing query suggested grasping configurations 9 and 29, while the connector picking query suggested configurations 9, 14, 16* and 27. All the grasps performed by operator for both of the analyzed tasks, are included in these results (an example of this can be seen in Fig 5, where grasps 9 and 29 are used for routing cables) which shows the high efficiency of the developed model for predicting the human behavior.

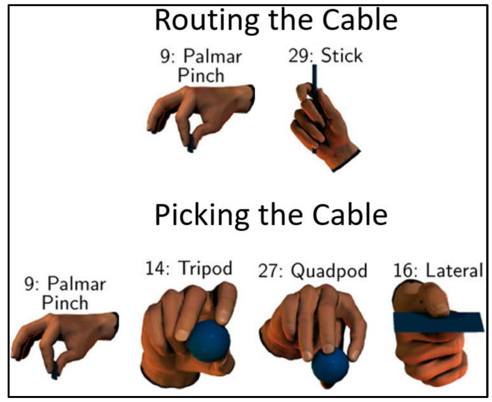

Fig 8. Results of tasks queries [23].

V. CONCLUSION

Grasping objects is an easy task for humans because of the high level of flexibility of the human hand and the high level of intellectual of the human, however implementing this behavior on a robot requires knowledge of the object and the task that is required to be performed. This problem can be solved via three steps including modeling the human behavior for grasping objects, selecting the proper gripper and designing the grasping approach for the robot. This paper presented an initial approach for the modeling the human behavior for grasping object.

The approach uses a modified version of the taxonomy for grasping objects by T. Feix,. In fact, the created taxonomy comprise of all the human grasp types that could be used for each combination of product (defined by its shape and some mechanical properties: weight, size, surface finish and rigidity) and task (just considering its general requirements of power or precision and some specific functionalities and constrains). Afterwards, an ontology model has been created for linking the product and the task with the proper human grasps for each situation. Subsequently, the ontology model has been populated with the values of the grasping taxonomy, materials and tasks. Finally, this ontology model was tested in a real use case of the REMODEL project. The next step, for future research, will be to improve the accuracy of the taxonomy, considering more specific tasks and materials. Additionally, the research will expand the functionality to include the selection of the robot gripper and the possible approaches that the robot can use for grasping the object.

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