Highlights

T-DOM: A Taxonomy for Robotic Manipulation of Deformable Objects

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- A taxonomy that qualitatively categorises deformation, motion, and interaction types in robotic manipulation of deformable objects.

- A novel distinction of bending deformation based on the structured or unstructured state of the object.

- Application of the taxonomy to segment and characterise diverse deformable object manipulation tasks.

T-DOM: A Taxonomy for Robotic Manipulation of Deformable Objects

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Abstract

Robotic grasp and manipulation taxonomies, inspired by observing human manipulation strategies, can provide key guidance for tasks ranging from robotic gripper design to the development of manipulation algorithms. Existing grasp and manipulation taxonomies, however, often assume object rigidity, which limits their ability to reason about complex interactions that occur during the robotic manipulation of deformable objects. To assist in tasks involving deformable objects, taxonomies therefore need to capture more comprehensively the interactions inherent in deformable object manipulation. To this end, we introduce T-DOM, a taxonomy that analyses key aspects involved in the manipulation of deformable objects, such as robot motion, forces, prehensile and non-prehensile interactions and, for the first time, a detailed classification of object deformations. To evaluate T-DOM, we curate a dataset of ten tasks involving a variety of deformable objects, such as garments, ropes, and surgical gloves, as well as diverse types of deformations. We analyse the proposed tasks comparing the T-DOM taxonomy with previous well established manipulation taxonomies. Our analysis demonstrates that T-DOM can effectively distinguish between manipulation skills that were not identified in other taxonomies, across different deformable objects and manipulation actions, offering new categories to characterize a skill. The proposed taxonomy significantly extends past work, providing a more fine-grained classification that can be used to describe the robotic manipulation of deformable objects. This work establishes a foundation for advancing deformable object manipulation, bridging theoretical understanding and practical implementation in robotic systems. Videos and supplementary material can be found at https://sites.google.com/view/t-dom.

Keywords: Deformable Object Manipulation, Taxonomy, Deformable Objects

1. Introduction

Robotic grasping and manipulation is a complex field due to the diverse challenges it encompasses, ranging from high-level scene understanding to the contact-rich interactions required for precise manipulation tasks. In this context, taxonomies have been used to provide structure and understanding of the problem. Examples range from classic grasp taxonomies [22, 33, 65] that are useful for gripper design and grasp choice decision-making to more recent manipulation taxonomies [9, 71] that define the type of interactions that can occur between the environment, the objects and the grasping agent, or the type of skills and tasks that exist [95]. Taxonomies and ontologies provide structure to complex problems, facilitating high-level decision-making, the development of more specialised low-level skills and the standardisation and benchmarking of the problem.

Existing taxonomies for manipulation have addressed various factors, including relative motion at contact points and between the object and environment [9], the use of single or multiple hands [51], the role of external forces in in-hand manipulation [23], and broader concepts of rigid-soft interactions [71]. However, these taxonomies have mainly focused on classifying key aspects relevant to the manipulation of rigid objects, overlooking how the object deforms when manipulated. In this work, we address this gap by incorporating an analysis of object deformation, which can facilitate the classification of diverse manipulation skills required for handling deformable objects.

The manipulation of deformable objects is of significant importance due to the ubiquitous presence of objects such as clothes, cables and food items in both everyday interaction scenarios and in industrial settings. Deformable object manipulation methodologies are however currently less developed compared to rigid object manipulation and pose significant challenges due to the high dimensionality of the object's configuration space. In order to manipulate these objects, the steps required to accomplish a task are highly influenced by the state of deformation, which may change with each interaction. While recent reviews of deformable object manipulation comprehensively cover the progress and ongoing challenges [57, 102, 109], few works have tried to classify in a systematic and descriptive way how the deformation affects the planning and execution of each manipulation step. One of the key limitations to identify the deformation of an object comes from the complexity of accurately measuring its state [61, 79, 102, 109], which often involves partial observability of the object. Existing approaches address this by using quantitative metrics that measure the deformation of objects such as ropes [56] or clothes [19], and qualitative metrics or labels that describe its state, e.g. identifying crossings in ropes [42], or the folded state of cloths [45, 35]. Due to the complexity of mapping diverse deformation modes to a quantitative metric, to build a taxonomy that can describe the deformation, this work adopts a qualitative classification that incorporates the forces in the manipulation task that produce the deformation.

In order to establish a framework for understanding robotic manipulation of deformable objects, this work proposes the Taxonomy for Deformable Object Manipulation (T-DOM), a taxonomy encompassing information about the type of deformation of the object, the robot manipulator motion, the end-effector grasp, as well as the interactions of the manipulated deformable object with the environment or the end-effector. The taxonomy is evaluated using a self-curated dataset of 10 tasks with varied manipulation actions and deformable objects. The analysis reveals that the proposed categories allow clear differentiation of manipulation strategies, even when the same object is subjected to varying deformations. Furthermore, our work discusses several applications for the proposed taxonomy including gripper design and learning of manipulation skills, along with future research directions.

Our main contributions can be summarised as follows:

- T-DOM: a taxonomy that qualitatively categorises deformation, motion and interactions in robotic manipulation of deformable objects, allowing for a systematic analysis of these tasks.

- A qualitative classification of bending deformation based on the structure of the object state, distinguishing between structured and unstructured bending to better capture the type of deformation.

- An analysis of the taxonomy, showcasing its effectiveness in identifying manipulation skills across tasks in a self-curated dataset and evaluating the critical role of deformation for this classification.

The paper is structured as follows. Section 2 reviews existing grasping and manipulation taxonomies and deformable object manipulation methodologies, covering how these address object deformation. In Section 3, the paper continues by providing fundamentals on deformation and the different types of deformation, together with the motion and interaction concepts on which the taxonomy is built. Then, Section 4 presents the proposed taxonomy, T-DOM, connecting and contrasting the categories of the taxonomy with prior taxonomies. After that, Section 5 introduces the proposed dataset tasks, demonstrating how T-DOM can be applied to classify the manipulation action sequences in these tasks, and contrasting the classification against prior manipulation taxonomies. Then, Section 6 discusses potential applications, limitations, as well as potential extensions of the proposed taxonomy. Finally, Section 7 concludes the paper.

2. Related Works

This section starts by providing a review and discussion of existing grasping and manipulation taxonomies, highlighting the gaps in the literature, followed by a short review of deformable object manipulation works and how these address the deformation of the object.

2.1. Manipulation Taxonomies

In the field of robotic manipulation, several taxonomies have been proposed to classify diverse aspects of grasping and manipulation. Cutkosky [22] developed one of the earliest grasp taxonomies, focusing on anthropomorphic grasp types for manufacturing tasks. This taxonomy classifies grasps based on the geometric and functional characteristics of the hand and the object, including criteria such as prehensility and grasp dexterity. Bullock et al. [9] expanded on this by introducing a hand-centric taxonomy that addresses both human and robotic manipulation. This taxonomy offers a detailed analysis of the contacts and motions involved in manipulation tasks, including characteristics such as the presence of motion at the point of contact. More recently, Krebs and Asfour [51] proposed a taxonomy for bimanual manipulation, addressing the complexity of using two hands simultaneously. This classification takes into account the coordination of the hands as well as spatial and temporal constraints. Nevertheless, these taxonomies assume that the manipulated object is rigid, and do not classify interactions with the object that may result in its deformation.

Few recent works have proposed classifications that also consider the manipulation of deformable objects. Borràs et al. [7] provided an analysis of the types of grasps used in cloth manipulation, considering the number of contacts and the geometries of the manipulation agents. However, this classification is restricted to grasps of textile materials, disregarding other aspects of manipulation such as the motion of the end-effector or the deformation of the object. Longhini et al. [58] proposed a taxonomy of textile objects considering material type and production method. While not a manipulation-focused taxonomy, it offers insights into how different textile properties influence robotic manipulation strategies. Paulius et al. [71] introduced a more generic motion taxonomy that takes into account the deformation of the manipulated object by classifying the engagement type as rigid or soft, and the outcome of the manipulation on the object that, if deformed, could exhibit a temporal or permanent deformation. More recently, Cuiral-Zueco and López-Nicolás [21] proposed a taxonomy of shape control in deformable objects. The taxonomy focuses on classifying the methods used for shape control by covering aspects such as the deformable object geometry, the deformation properties, and the control strategies utilised. It is important to note that this is not a manipulation taxonomy such as the ones proposed by Bullock et al. [9] or Paulius et al. [71], and for this reason, it neglects aspects such as the robot motion or the grasping of the object.

Although the aforementioned taxonomies have provided comprehensive classifications of grasping and manipulation tasks, these have not incorporated important aspects relevant to the manipulation of deformable objects, such as the type of deformation. Our proposed taxonomy addresses these gaps by classifying the type of deformation based on the forces involved in deforming these objects. In addition, our work categorises the robot motion during the manipulation, as well as the interactions between objects and their environment, which are critical in real-world manipulation tasks involving deformable objects.

2.2. Types of Deformation Under Manipulation

The robotic manipulation of deformable objects involves different types of deformation, such as compression, tension, or bending.

Compression in volumetric objects typically arises when opposing forces act to reduce one or more of the objects' dimensions. This type of deformation can be observed in various scenarios, ranging from grasping of objects such as sponges while tracking their deformation [20, 69], to manipulating a broader range of objects such as plush toys or dough [81]. Compression can be also observed in tasks that require tools, such as those performed during the preparation of dumplings [83].

Tension occurs when opposing forces stretch a deformable object along an axis. It plays a key role in tasks such as the identification of garment properties [58], where it can appear along with torsion deformation. Several works utilise dynamic manipulation techniques to unfold garments, where tension arises as the cloth
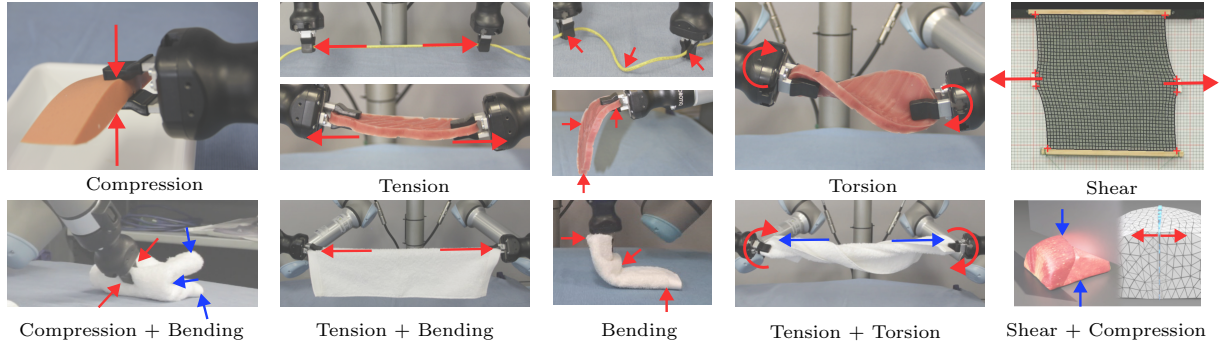
Figure 1: Robotic manipulation of multiple deformable objects showing compression, tension, bending, torsion and shear deformation, as well as possible combinations of the deformations. The shear deformation shows a cloth from the open-source dataset provided by Wang et al. [93]. The combined deformations red and blue arrows refer to the first and second deformation, respectively. The shear and compression example shows slicing a piece of meat in simulation [38].

is stretched in the air [36, 106]. Tension can also occur along with other deformations. For example, it can also appear with bending while manipulating soft tissue [41] or volumetric objects [100]. Similar tension and bending deformation can be observed in assistive dressing, where the robot pulls a garment sleeve while the user anchors its end [110].

Bending is one of the most common types of deformation in the manipulation of deformable objects. It appears in the manipulation of 1D deformable objects such as cable routing [59], string or wire insertion [73, 94, 98], needle threading [105], and rope manipulation [1, 60, 89, 103, 111]. For 2D deformable objects, it appears in tasks ranging from cloth folding [54, 67, 91, 92], unfolding [6, 32, 36], or placement [63], to paper manipulation [107]. Finally, bending is also critical for controlling the shape of 3D volumetric objects [25, 76, 82, 88, 99].

Other less frequently studied types of deformation include torsion and shear. Torsional effects, such as twisting along the longitudinal axis, have been modeled in deformable linear objects by Saha et al.[77, 78]. Shear deformation, which involves lateral displacement within the object, typically arises while cutting volumetric deformable materials [44, 72]. The limited exploration of these deformation modes highlights a promising direction for future research.

This paper presents a classification and analysis of the aforementioned types of deformation commonly observed in tasks studied within deformable object manipulation research.

3. Properties of Deformable Object Manipulation

This section introduces three key aspects of manipulating a deformable object that serve as the foundation for developing the proposed taxonomy: the concept and types of deformation, the motion during manipulation and its relationship to energy changes of the manipulated object, and the interactions between the manipulated object and its surroundings.

3.1. Deformation Concepts and Terminology

The term *deformation* is extensively used in the context of robotic manipulation of deformable objects, encompassing various aspects such as perception, modelling, and control [40, 2, 102]. However, throughout these works the concept of deformation is ambiguous and left to the reader to conceptualise.

The Dictionary of Engineering defines deformation as *"any alteration of shape or dimensions of a body caused by stresses, thermal expansion or contraction, chemical or metallurgical transformations, or shrinkage and expansions due to moisture change"* [64]. This definition opens a wide spectrum involving thermal, chemical, and metallurgical transformations. These transformations can often be neglected when performing robotic manipulation of deformable objects by assuming constant environmental conditions. Sanchez et al. [79] state that "a deformation occurs when an external force applied to an object results in the object
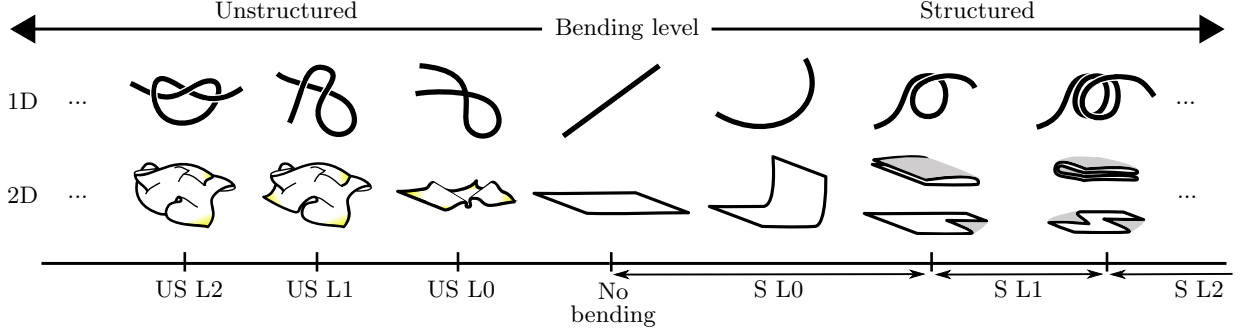
Figure 2: Qualitative classification levels for bending deformation as structured or unstructured for 1D and 2D deformable objects. The structured level is classified by loops and *g-folds* [67], for 1D and 2D objects, respectively. The unstructured level is classified by knots for 1D objects, and as the number of accessible corners for a cloth flattening task.

changing its shape". More generally, deformation refers to any change in the shape of an object. For a known object, it is considered deformed if its shape differs from a predefined canonical shape [11, 17]. Conversely, if the object retains its canonical shape, it is considered as not deformed. However, in the absence of prior knowledge of the object's shape, deformation is identified by any deviation from an initially observed object shape.

In this work, we assume that the forces that deform an object in a robotic manipulation task can originate from: 1) a robot manipulator, 2) a tool manipulated by a robot, or 3) objects in the environment interacting with the manipulated object. Considering the forces that a robot applies during grasping, or while performing a motion to complete a task, it seems intuitive to relate these forces to the object deformation they can induce. Following this, deformation can be characterised by the direction of the applied forces (see Figure 1). The type of deformation can be classified as compression, tension, bending, torsion, and shear [10]. A detailed definition of these deformations is provided below, accompanied by examples of common tasks in robotic manipulation tasks.

Compression. This deformation results from applying two opposite forces towards the object along a specific axis, causing the object to shorten in the direction of the applied forces. This deformation can also occur when applying a single force to an object placed on a surface in the direction perpendicular to the surface. This type of deformation is common when shaping volumetric deformable objects [84]. As pointed out by Sanchez et al. [79], 1D and 2D deformable objects such as ropes and textiles are characterised as objects without compression stress. This follows from the fact that these objects are usually modelled following an incompressibility assumption [46]. However, for certain deformation configurations such as a folded or stacked 2D object, the object has significant volumetric structure and in such cases, the assumption of incompressibility can be relaxed, allowing 2D objects, such as cloth, to undergo compression deformation, e.g. grasping a folded cloth, see Figure 1.

Tension. This deformation can be seen as the inverse of compression. Given one fixed point on the object such as a grasping point, tension is generated when a force is applied away from the object, stretching the object along the axis of such forces without tearing it. This deformation is common when a deformable object is stretched, for example, when placing a tight cover on a chair or a bed sheet, stretching a cloth in the air for placing it flat on a table [36], and when knotting ropes [53] or plastic bags [34].

Bending. Also referred to as flexural deformation, this deformation appears when applying an external force perpendicular to the object's longitudinal axis, causing it to curve. The Dictionary of Engineering defines bending as the deformation of points in an elastic body that were originally straight, causing them to displace and form a plane curve [64]. Notably, even after the external force is removed, the bending deformation can persist due to the internal forces within the object, which may prevent it from returning to its original shape. We refer the reader to the existing literature on deformable object modelling [2, 18, 40], which provides a

detailed explanation of how these internal forces can be approximated using different mathematical models. Consequently, bending is a common deformation encountered in deformable object manipulation tasks, such as shaping ropes and clothes [16].

Torsion. A torsional or twisting deformation is generated when a torque is applied around the longitudinal axis of the manipulated object, given that the axis is fixed in one of its sides. This can occur as well when two torques are applied in opposite directions along the longitudinal axis of the object. Similarly to the compression deformation, 1D and 2D deformable objects can also be subjected to this deformation when they possess sufficient volumetric structure. This deformation can be seen when twisting a thread [77], or wringing out a sponge or a towel to dry it out [4], see Figure 1.

Shear. A shear deformation is caused when two external forces are applied in opposite directions along two distinct parallel lines of the object [64]. Manipulation actions that cause shear deformation are common when cutting objects [44, 86, 90], which usually occurs along with compression deformation, as shown in Figure 1. Furthermore, shear deformation can commonly be seen when performing system identification [93]. In textiles, the elasticity along different pulling lines may differ dramatically due to fabrication processes. That elasticity along diagonal lines is an important parameter to consider in this particular setting. Shear deformation can also be observed on volumetric deformable objects, such as meat [72]. Nevertheless, this deformation is less common in 1D and 2D deformable objects, where usually the plane section principle is followed and therefore shear deformation is neglected [104].

The concepts of compression, tension and torsion can be intuitively understood as squeezing, stretching and twisting an object, respectively, and can therefore be clearly identified when manipulating deformable objects. However, while the concept of bending is widely utilised in the literature [54, 81, 88], it does not provide direct insight of the shape or state of the object. For instance, both a crumpled and a folded cloth exhibit bending deformation, yet their shapes are essentially different. The challenge of defining bending deformation arises from the infinite number of degrees of freedom in deformable objects, where the internal forces can generate small localised curvature changes in the object.

Consequently, it is challenging to categorise the deformation of an object simply as bending to understand the object state. To identify different bending deformation cases, we introduce two concepts: *structured bending* and *unstructured bending*, depicted in Figure 2. These types of bending deformation are characterised by the structural arrangement of the deformation. If ordered bends exist, as happens when folding, we call the bending structured. On the contrary, if the bending deformation is chaotic or wrinkled, we call it unstructured. It is important to highlight that here unstructured does not imply the absence of an underlying structure in the deformation. Instead, this refers to the fact that the resulting patterns cannot be easily captured or described by analytical expressions. Given the distinct nature of 1D and 2D deformable objects, we provide separate metrics to recognize the degree of structuredness.

Structured Bending. To quantify the level of structure in a bending deformation we count the number of loops or folds as metrics for 1D and 2D deformable objects, respectively. We can define a fold as *g-folds* as proposed by Miller et al. [67]. Any bending before a full loop or fold is done will be labeled as $L0$ structured bending. In 3D objects, the structured bending is measured in the plane curve where the bending deformation takes place and will remain normally on the $L0$ level.

Unstructured Bending. The idea is to measure the level of unstructuredness by how much one needs to manipulate the object to remove the bending. That is, displacing the points that form a plane curve to their originally straight configuration. For 1D objects, we propose to count the number of visible crossings. For 2D, the manipulation required to flatten an object is usually related to being able to grasp certain keypoints, such as the shoulders of a T-shirt or the corners/edges of a napkin. Therefore, we propose to measure unstructured bending deformation by the number of graspable or accessible keypoints (see Figure 2). When all keypoints are graspable, but the object is wrinkled, we will assume that is the first level $L0$ of unstructured bending.

Both structured and unstructured bending deformations can take place at the same time. For example, a rope can present loops on one end as well as crossings and tangles on the other end, and cloths can present g-folds as well as unstructured wrinkles.

It is important to note that all the deformations aforementioned can take place when materials work in their elastic or plastic region of the stress-strain curve. Thus, classifying deformations using these concepts is valid for the manipulation of objects such as garments working in their elastic region, as well as plastic deformation in objects such as dough [83].

3.2. Energies during Manipulation Motion

The manipulation of a deformable object can be conceptualised as determining the configuration of exerted forces that brings the object to the desired state. Prior works on deformable object manipulation have addressed the optimisation problem of finding the motion to reach the desired minimum-energy state or identifying the robustness of a grasp from an energy perspective [8, 27, 28]. In this context, the end-effector motion can be prescribed based on the predominant energies of the object when moved from one state to the desired one. These energies are the kinetic and potential energy of the object, where the latter can be further divided into gravitational potential energy and elastic potential energy. While recent works simplify the problem of finding the minimum energy-state motion by using e.g. predefined motions that neglect the associated energies [36], these approaches share the underlying goal of moving the object into the desired state.

In this work, we relate the energies of motion to the manipulation classification by Mason [62]. Here, *dynamic manipulation* is defined as manipulation tasks dominated by inertial forces, that is, the acceleration and mass of the object. Hence, the motion is dominated by the kinetic energy of the manipulated object. By contrast, *quasi-static manipulation* is defined as tasks dominated by frictional and impact forces, neglecting inertia. In deformable object manipulation, tasks that require transporting the object or performing pick-and-place motions are defined as quasi-static, which are dominated by the gravitational energy. Similarly, tasks where the success depends on the elasticity of the deformable can be defined as quasi-static, which are dominated by the elastic energy of the object. This energy is particularly relevant in deformable objects like elastic rods, whose manipulation can be formulated as the optimisation of the elastic energy of the rod [8].

In addition, Mason classifies manipulation as kinematic or static. In this work, we neglect these two categories since deformable object manipulation tasks cannot be described uniquely by the kinematics of the end-effector, and the friction of the object due to collisions and self-collision needs to be taken into account even when performing what is denoted as static manipulation.

3.3. Interactions

Robotic manipulation is accomplished through physical interactions of the robot with the target manipulation object. This interaction can be defined as *prehensile* if the end-effector contact forces with the object can stabilise it without external forces. By contrast, if the interaction involves forces such as gravity or a reaction force from a contact with the environment the interaction is denoted as *non-prehensile*. Grasping an object can be achieved by either prehensile or non-prehensile grasps. Prehensile grasps for rigid objects have been extensively studied and classified in works like [22] and [33]. Cutkosky [22] further classified grasps by their purpose or function, distinguishing between power and precision grasps, while Feix et al. [33] categorised grasps based on the number of fingers involved in exerting the opposite forces. On the contrary, the diversity of prehensile grasps for deformable objects has been less actively studied, partly because a pinch grasp usually suffices to perform a wide range of deformable object manipulation tasks. Borràs et al. [7] introduced a framework to classify textile grasps based on the geometry of the contact patches, showing that although pinch grasps are common, more complex grasps play a significant role in dynamic manipulation. This framework included both environmental and robot end-effector contacts, as well as bi-manual grasps.

Non-prehensile interactions using contacts with surfaces of the environment have been largely considered in the literature for rigid objects, such as in [9, 23, 31] and less frequently addressed for deformable objects [7]. Additionally, research has explored combinations of prehensile grasps with environmental contacts [12]. Furthermore, non-prehensile grasps using acceleration forces present more challenges. These are
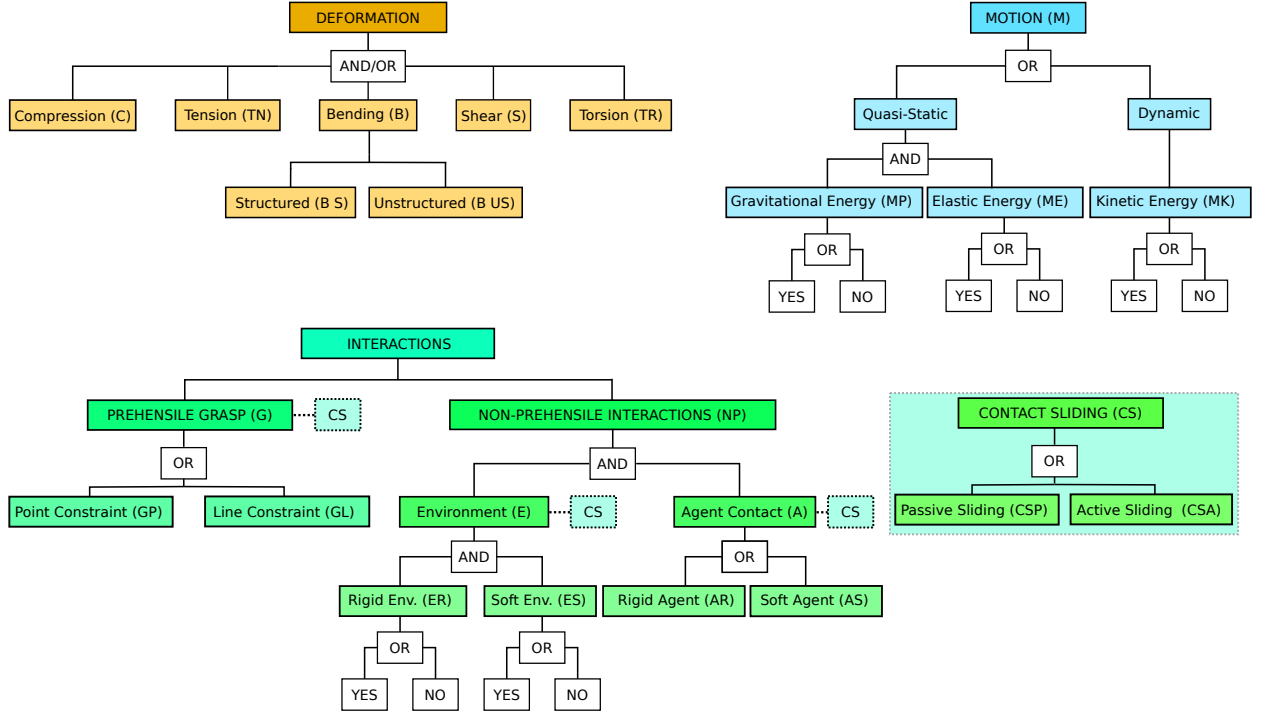
Figure 3: The proposed taxonomy is composed of deformation (D), motion (M), and interactions. The interactions are classified as prehensile grasp (G) and non-prehensile interactions (NP), and contact sliding (CS) as a special case of interaction that can take place in both prehensile grasps as well as each sub-category of non-prehensile interactions, shown by a dashed line connecting the CS block. Each sub-category is shown with its associated short tag.

considered in the context of extrinsic dexterity [23], which refers to the use of any external forces to enhance manipulation. All in all, these concepts are used to build the classification developed from Section 4.3 to Section 4.5.

4. A Taxonomy for the Manipulation of Deformable Objects

This section describes T-DOM, a taxonomy for robotic manipulation of deformable objects, depicted in Figure 3, which includes short tags associated with each category of the classification. The taxonomy is divided into three main categories: object deformation, robot motion, and interactions. For clarity, Table 1 provides a comparison of the categories and sub-categories from our proposed taxonomy with those from existing grasping and manipulation taxonomies. The remaining sections will explain how the proposed categories compare to the related literature.

4.1. Deformation Classification

The types of deformation considered in T-DOM build on those introduced in Section 3.1. In addition to compression ($\mathbf{C}$), tension ($\mathbf{TN}$), torsion ($\mathbf{TR}$), and shear ($\mathbf{S}$), we distinguish between different levels of structured bending and unstructured bending. The first structured bending level ($\mathbf{S\ L0}$) identifies the transition from no bending deformation to one loop or g-fold. The subsequent structured levels refer to increasing the numbers of loops or g-folds, e.g. $\mathbf{S\ L2}$ refers to either 2 loops or 2 g-folds. For unstructured bending, the qualitative metrics are discrete. As previously discussed, for 1D objects the first level ($\mathbf{US\ L0}$) is defined by crossings, and for 2D objects by almost flat clothes with wrinkles, where all keypoints are visible. Further levels of unstructured follow Fig. 2.

Furthermore, we also address several combinations of these deformations, which often occur simultaneously during the manipulation of deformable objects. Below are a few examples:

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- **C+B: Compression & Bending.** In the example shown in Figure 1, the towel is folded (bending) and the grasp performed to pick it up compresses it.

- **TN+B: Tension & Bending**. For instance, this occurs when pulling a cloth in the air from its edges, see Figure 1, where bending occurs naturally due to the internal forces of the cloth. Another example can be seen when folding a piece of cloth while applying tension at the grasped points to prevent wrinkles [53].

- **TN+TR: Tension & Torsion**. In Figure 1, a twisted towel undergoes torsional deformation when wrung by a bimanual system. At the same time, the robots apply tension by pulling the towel in opposite directions.

- **S+C: Shear & Compression**. As shown in Figure 1, the simultaneous shear and compression deformation is common when cutting deformable objects [38].

As discussed in Section 2, this classification provides a more comprehensive understanding of object deformation than prior taxonomies, which either overlook deformable objects or fail to account for the forces driving the deformation, limiting their ability to differentiate between different types of deformation, see Table 1. While T-DOM does not explicitly address plastic and elastic deformation as in prior taxonomies [21, 71], the deformation types covered in the classification can identify deformations that occur in both cases. Additionally, Section 6 discusses potential extensions of the taxonomy to include e.g. failure modes.

Table 1: Comparison of categories and sub-categories covered by grasping and manipulation taxonomies found in literature and the proposed taxonomy. The categories are divided into distinctions of bimanual manipulation, robot motion, prehensile grasp, interactions and deformation of the manipulated object. Note that we include in this table the taxonomy proposed by Cuiral-Zueco and López-Nicolás [21], which is not a manipulation taxonomy but rather a taxonomy for comparing shape control methods, but we include it for completeness.

Category	Sub-category	[22, 33]	[9]	[7]	[71]	[51]	[21]	**Ours**
	Bimanual Manipulation	✗	✓	✓	✓	✓	✗	✓
Robot Motion	Trajectory	✗	✓	✗	✓	✗	✗	✗
	Energy	✗	✗	✗	✗	✗	✗	✓
Prehensile Grasp	Anthropomorphic	✓	✓	✗	✗	✓	✗	✗
	Nr. Contacts	✓	✗	✓	✗	✗	✗	✓
	Robotic	✗	✓	✓	✗	✗	✗	✓
Interactions	Motion at Contact	✗	✓	✗	✗	✗	✗	✓
	Non-Prehensile	✗	✓	✓	✗	✗	✗	✓
	Rigid/Soft	✗	✗	✗	✓	✗	✗	✓
	Contact Duration	✗	✗	✗	✓	✗	✗	✗
Deformable Objects	Objects	✗	✗	✓	✓	✗	✓	✓
	Elastic/Plastic	✗	✗	✗	✓	✗	✓	✗
	Force Direction	✗	✗	✗	✗	✗	✗	✓

4.2. Motion Classification

For the proposed taxonomy, following the definitions outlined in Section 3.2, we introduce the following classification:

- **MK: Motion → Kinetic**. This includes dynamic motions as described in the previous section, dominated by inertial forces. Some examples include swinging a cloth to unfold it [36], or hitting a target with a rope [16].

- **ME: Motion → Elastic** This includes quasi-static manipulations where the task success depends mostly on the elastic forces of the object. Examples include shaping a rope [8] or a volumetric object [84], and securing a mask string [28].

- **MG: Motion → Gravitational**. This tag includes quasi-static manipulations where the elasticity of the object can be neglected. Examples include transporting a cloth to store it [101] or motions performed to approach the object.

- **MGE: Motion → Gravitational-Elastic**. These are cases where both elastic and gravitational energies play a role in deformable object manipulation. For instance, [28] present a scenario where a fish is lifted from a table using a scoop. While the scoop containing the fish is lifted up, the fish is subject to elastic force due to the deformation of its body under gravity, accompanied by a change of gravitational energy.

Compared with the taxonomy definition (*motion* and *no motion*) in [9], we further sub-categorise *motion* in finer granularity. By contrast, our classification is less detailed than the one proposed by [71], which classifies the different prismatic and revolute axes of the motion trajectory.

4.3. Prehensile Interaction Classification

Building on the definitions presented in Section 3.3, we classify interactions into prehensile grasps and non-prehensile interactions. In this work, prehensile grasps are defined using a variation of the prehension geometry framework from [7]. Rather than focusing on the geometry of the contact patches that generate the opposing forces defining the grasp, we categorise grasps based on the geometry they constrain on the object. Hence, the classification proposed for prehensile grasps is as follows:

- **GP: Grasp → Point.** Pinch grasps are a clear example of grasps that constrain a point, where the position of a single point on the object is controlled.

- **GL: Grasp → Line.** Constraining the position of a line of an object can be used to perform tasks such as cloth folding more efficiently [87] or to fold in the air [7].

These categories can be further extended to more complex geometries as in the taxonomy by [7], which is the only prior taxonomy that does take into account the number of contacts in prehensile interactions of deformable objects. However, for simplicity, our classification is restricted to the geometries that can be constrained with parallel jaw grippers, which are more common in deformable object manipulation tasks.

4.4. Non-Prehensile Interactions Classification

In this work, non-prehensile interactions are classified into contacts of the manipulated object with the *environment* or with the *agent* that manipulates the object. Furthermore, we distinguish between interactions made by a soft or rigid object, similar to [71].

Non-Prehensile Agent Contact. This category encompasses interactions performed by the robot hand with external forces. Specifically, this category refers to grasps where one of the opposing forces is applied by an agent (robot or tool), while the other force may originate from the environment or gravity. Examples of this category include basket grasps [85] or pressing an end-effector against a table for flattening a cloth. A caging grasp may happen without any contact [26], however, we consider they are manipulating the object because they constrain the pose of the object. Therefore, we classify caging as a non-prehensile agent interaction.

The agent contacts are classified into rigid or soft as:

- **N-P.AR: Non-Prehensile → Agent Contact → Rigid**. When the agent is rigid, such as rigid grippers or tools like shovels [28].

- **N-P.AS: Non-Prehensile → Agent Contact → Soft**. When the agent is soft, like with soft robot hands or when using deformable tools like could be a plastic bag to carry objects [14] or using deformable scoops the bend when they touch the table.

Non-Prehensile Environment. This category refers to grasps where both opposing forces are exerted by extrinsic forces, which may be gravity or contacts with the environment. Such passive interactions are very important for the manipulation of deformable objects because they are highly used to conform shape to the objects, also when no other agent contact happens. Therefore, we consider the environment as an additional virtual finger as done in other extrinsic dexterity papers such as [12]. The non-prehensile environment interactions are classified as follows:

- **N-P.ER: Non-Prehensile → Environment → Rigid**. This includes interactions with rigid surfaces, such as an object resting on a table.

- **N-P.ES: Non-Prehensile → Environment → Soft**. Examples of this category are interactions of the deformable object with other deformable objects, e.g. a towel placed on a pile of towels.

- **N-P.ERS: Non-Prehensile → Environment → Rigid & Soft**. Both types of environment interaction —rigid and soft— can occur simultaneously. For instance, a set of grapes partially wrapped in an elastic protective cover lying on a hard tray surface demonstrates both rigid and soft environment contacts.

4.5. Contact Sliding

Along with the aforementioned interactions, our taxonomy classifies one special case that is notably relevant in deformable object manipulation, which is contact sliding. It is conceptually equivalent to the category of motion at contact discussed by Bullock et al. [9] for rigid objects. This interaction can be seen when sliding a robot end-effector on a cloth to find its edge e.g. unfolding the garment [74], or sliding through a cable for its posterior insertion [80]. In cases where motion at contact exists, the contact point on the robot end-effector usually remains unchanged, but the points on the object translate or rotate with respect to a fixed contact frame on the robot. In deformable object manipulation, we primarily consider translational motion at contact, i.e. sliding at contact, although a rotation could also be possible, and appears in rigid object in-hand manipulation as pivoting. Sliding is a characteristic of every contact, therefore, it is a branch of the taxonomy that connects to both prehensile grasping, environment and agent contact interactions, see Figure 3. The category of contact sliding is classified as follows:

- **CSA: Contact Sliding → Active**: Active sliding takes place when the manipulated object remains static while the end-effector moves, modifying its contact points with the object without grasping it. Some examples include and end-effector grasping and sliding along an edge of a cloth [50] or the tip of an end-effector sliding along the surface of a cloth to flatten it.

- **CSP: Contact Sliding → Passive**: Passive sliding occurs when the end-effector remains static at the contact and the object slides pulled by an external force, such as another robot arm or gravity. An example could be an object falling from a platform grasp.

4.6. Bimanual manipulations

All categories describing end-effector actions such as motion, grasps, or active contacts refer to a single robot arm. However, many deformable object manipulation tasks can be performed more effectively using a bimanual system [1, 36, 106]. Rather than creating duplicated categories in T-DOM, as in [7, 51], we propose to decouple the tags for each arm involved in the task, e.g. left and right arm. Further details about this decoupling are provided in Section 5.2.

5. Taxonomy Application

This section presents how the proposed taxonomy can be applied to classify deformable object manipulation tasks, demonstrating the importance of classifying the deformation for understanding the task. The section starts by introducing ten deformable object manipulation tasks, detailing the robot motions and interactions with objects. Next, it outlines the methodology used to classify the manipulation actions within

these tasks according to the proposed taxonomy. Finally, it describes the experiments performed to analyse the taxonomy, which evaluate the impact of incorporating deformation as a key category alongside the other categories.

5.1. Deformable Object Manipulation Dataset

To consider all the interactions of the deformable object with the robot and its surroundings, as well as the motions of the robot, we take inspiration on [9] and analyse the transitions during robot manipulation tasks. For such analysis, all the steps that take place during the manipulation of a deformable object need to be recorded. Despite the availability of open-source datasets such as the Daily Interactive Manipulation dataset proposed by Huang and Sun [43], current datasets either show only one stage of the manipulation, such as the action of lifting or transporting an object, or have limited deformable object manipulation tasks [68, 47]. Thus, we recorded ten deformable object manipulation tasks, five of them using the UR5 robot, and five of them using hand-held grippers. The set includes five bimanual manipulation tasks and five unimanual tasks. For each task execution, we recorded RGB-D data using a Microsoft Azure Kinect. The analysed tasks can be described as follows.

Task 1: Fold towel. The robot grasps a folded towel by sliding under its side to clamp an edge. It then performs a quasi-static motion to fold the towel in half before releasing it.

Task 2: Transport towel. The robot approaches a folded towel and slides beneath it to clamp it, as in task 1. It then lifts and transports the towel, placing it onto a stack of towels.

Task 3: Wring out towel. Two robots approach a towel lying flat on a surface, sliding the end-effectors underneath to grasp it by the edges. Then, they lift the towel and apply a twisting motion to simulate wringing out water.

Task 4: Cloth Edge Tracing. In the starting configuration, one robot grasps a corner of the cloth while a second one holds the cloth near its edge. First, the robot grasping the corner moves away from the other manipulator, causing the cloth to passively slide at the edge grasped by the second robot. Once this motion stops, the second robot moves away, actively sliding along the edge while the first robot remains stationary.

Task 5: Transport meat. The robot approaches a meat-like silicone piece, slides its gripper underneath to clamp it securely. Then, the robot lifts and transports the piece to place it on a tray.

Task 6: Cloth flattening. In this task, a hand-held gripper approaches a cloth with two visible corners. The gripper grasps the cloth by one corner, lifts it, and places it. Finally, the gripper slides out of the cloth, leaving three visible corners.

Task 7: Unfold medical gown. Two hand-held grippers hold by the collar a partially unfolded medical gown. A human performs a dynamic shaking motion, to fully unfold the gown.

Task 8: Bag opening and item insertion. Similar to task 7, two hand-held grippers hold an initially crumpled bag by the handles. A human performs a dynamic motion to open it. Finally, a rigid object is inserted into the bag.

Task 9: Open surgical glove. Initially, a glove is in a crumpled configuration inside a box. One hand-held gripper is inserted into the box to pinch and lift the glove. Once lifted, a second gripper grasps the wrist border of the glove. The first gripper releases the glove, and re-grasps it from the opposite side of the wrist. Finally, both grippers move to open the glove.

Task 10: Cable looping. In the starting configuration, a cable is grasped by a hand-held gripper. The gripper moves to hang the cable onto a second gripper, which secures the cable while the first gripper forms a loop. Once the loop is created, the second gripper is opened to hang the loop.

To simplify the collection of data for these challenging tasks, the initial configuration of the objects is fixed, the trajectories of the UR5 robots are pre-defined, executed in an open-loop fashion, and the hand-held grippers are operated by a human. The initial configuration of the objects, the interactions, the motion of the grippers, and the selected unstructured deformation keypoints, can be seen on the project website[1]. The tasks have been designed to cover at least the basic types of deformation, except shearing, which is less common in manipulation tasks. The compression deformation takes place in tasks 1, 2, 5 and 6; tension in tasks 3, 4 and 9; torsion in task 3; and either structured or unstructured bending in all tasks. In addition, the tasks have been designed to include commonly studied manipulation tasks, encompassing a diverse range of actions and trying to maximise the variety of manipulation skills required.

5.2. Task Segmentation and Representation

The tasks described in the previous section are composed of a sequence of sub-tasks or actions, each of which can be described by T-DOM tags. To identify the segmentation induced by T-DOM, we manually annotate the time instants in which a robot action creates a change in any of the taxonomy categories. Since our goal is to evaluate the validity of T-DOM to classify deformable object manipulation, we assume visually observable deformations and interactions via the dataset RGB data. We discuss limitations and potential future work in Section 6.

The resulting segmentation for Task 1 is shown in Figure 4, and for Tasks 2 and 4 is shown in Figure 5, while an overview of the segmentation for all tasks, along with their corresponding tags, is provided in Appendix A. To distinguish between the left and right manipulators in bimanual tasks, the tags are written on the left and right side of the category, accordingly. For unimanual tasks, we retain both tags but set the second manipulator to a none tag, ensuring that all taxonomy tags have the same structure, regardless of the number of manipulators.

In order to evaluate the contribution of our proposed taxonomy to the state-of-the-art, we compare it against the taxonomies proposed by Bullock et al. [9] and Paulius et al. [71]. The Bullock taxonomy was created to represent dexterous manipulation, with special attention to in-hand manipulation. Although it is defined as a decision tree, it can also be described in tags with the following categories:

- **Contact Category**: Contact Non-Prehensile (C NP); Contact Prehensile (C P); No Contact (NC).

- **Motion Category**: Motion within hand (M W); Motion not within hand (M NW); No Motion (NM).

- **Slippage category**: Motion at contact (A); No motion at contact (NA); No contact ("-").

Note that it is assumed that arm motion and motion within hand will not happen simultaneously.

For the taxonomy of Paulius et al. [71] the trajectories of the robot or hand-held grippers as well as the manipulated object are classified by the corresponding number of moving axes. Furthermore, the type of interaction distinguishes between contacts of the manipulator with rigid surfaces (rigid discontinuous), contact with the deformable object (soft discontinuous), and the object that is grasped (soft continuous). Finally, all the manipulation tasks involve objects working in their elastic region of the stress-strain curve, and therefore, our tasks involve either no deformation or temporary deformation of the object.

To better compare with these taxonomies, Figure 4 and Figure 5 also show the segmentations induced by our T-DOM, Bullock's and Paulius, that act as baselines. The actions in task 1, shown in Figure 4, involve: approaching and releasing the object (Q.Grav), folding the object (Q.Grav/Elast), a continuous contact with the rigid table (N-P.R), and a non-prehensile contact with the gripper (NP.A R) when it slides beneath one side of the cloth to clamp it (CS active). In terms of deformation, the cloth is initially folded with a single g-fold (structured bending level 1), grasping the object results in compression deformation within

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[1]Project website: https://sites.google.com/view/t-dom

the cloth, and the folding action increases the structured bending level to SL2. While the segmentation remains the same across all taxonomies, there are several key differences. Firstly, passive contacts with the environment are not considered in the baselines. For example, the Bullock taxonomy describes the folding action equally as any object transfer, that is, a grasp in motion. In contrast, T-DOM provides a more detailed representation. In addition to the grasp in motion, it includes a description of the point grasp, the passive contact with the environment, and a change in deformation. Secondly, throughout all the manipulation steps Paulius et al. [71] classifies the deformation invariant, as the object is temporarily deforming. Therefore, the action of folding does not produce any change in their deformation category.

In the transport task shown in Figure 5-a, the structured bending deformation remains constant due to the folded configuration of the fabric. However, placing a folded object requires a placing strategy involving an environmental contact between the object and the placing location. This interaction introduces a segment between the actions 4 and 5. In particular, this segment is not present in the Bullock et al. [9] taxonomy, as it does not account for passive environmental contacts.

The classification differences with Paulius et al. [71] taxonomy become more pronounced when examining the action of edge tracing in Figure 5-b. Here, Paulius et al. [71] classification shows three constant categories, which refer to the motion of both robots which are in constant contact with the cloth, temporally deforming the object. Therefore, Paulius' taxonomy provides only one segment. Both T-DOM and Bullock et al. [9] taxonomy are able to distinguish between actions T5-2 tracing (static) and T5-3 tracing (motion), where contact sliding or motion at contact plays a crucial role. In addition, our classification enables us to distinguish the change in the structure of the cloth which starts unstructured (US L1) and transitions to structured bending deformation (SL0) once the task is complete.

Overall, the classification using T-DOM provides similar granularity to [9] when segmenting the tasks,

Figure 4: Analysis of the transitions of Task 1: Fold Towel using the proposed taxonomy, T-DOM, as well as Paulius et al. [71] and Bullock et al. [9] taxonomies, showing only the categories that show any change. Since the towel is manipulated on a table the T-DOM no-zero constant category (omitted) is NP Env (R). For all tasks, the structural outcome according to Paulius et al. [71] taxonomy is deforming temporarily, and therefore it is omitted for simplicity.

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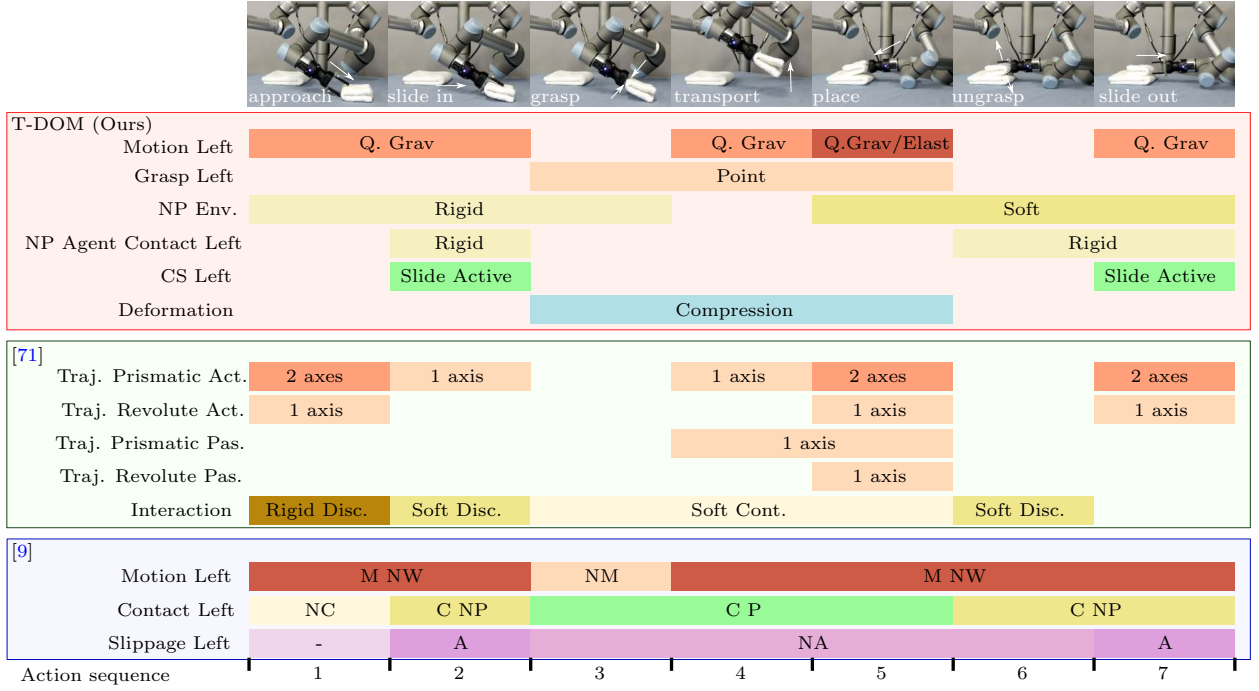
(a) Task 2: Transport Towel. T-DOM no-zero constant category is Struct. Bending (S L2).
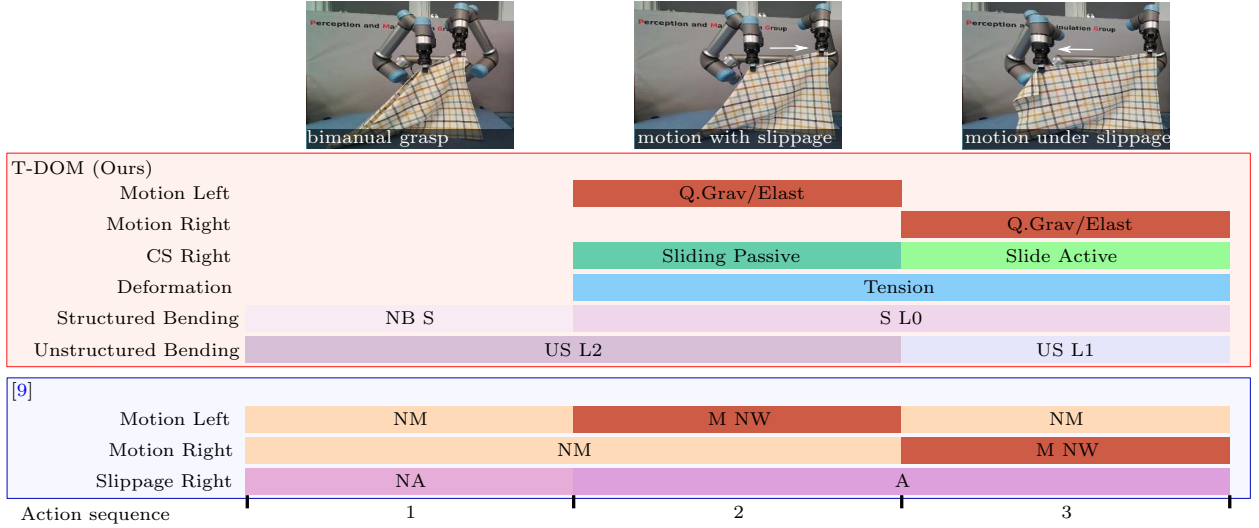
(b) Task 4: Edge tracing. T-DOM no-zero categories are left and right grasp (P and P) and NP Env (R). Paulius et al. [71] categories are omitted since all are constant during the manipulation actions.

Figure 5: Analysis of the transitions of Task 2, and Task 4 using the proposed taxonomy, T-DOM, as well as [71] and [9] taxonomies, showing only the categories that show any change. For all tasks, the structural outcome according to Paulius et al. [71] taxonomy is deforming temporarily, and therefore it is omitted for simplicity.

except in the tasks involving passive contacts, like placing an object. Here, a first contact with the environment is used to place the deformable object, like in task 2. More importantly, the classification using Paulius et al. [71] and Bullock et al. [9] taxonomies provide less understanding of the transitions the robot needs to accomplish the task since the deformation phases are disregarded in the classification.
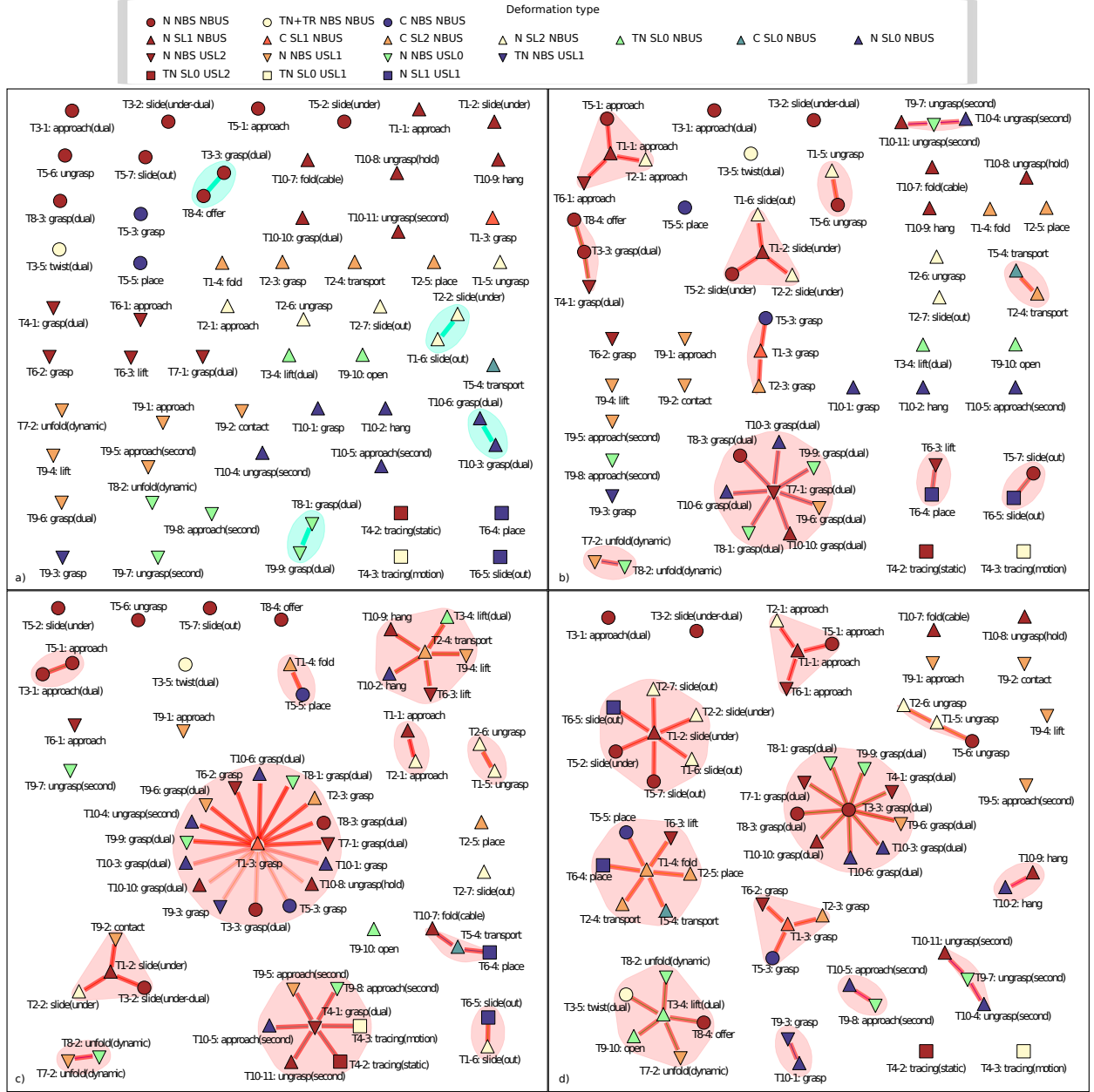
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Figure 6: Graph clustering of manipulation actions in the proposed dataset for a) T-DOM, b) T-DOM without deformation, c) [71] taxonomy, and d) [9] taxonomy. The nodes represent the action-IDs and the edges action-IDs which share the same tag according to the evaluated taxonomy. The colours of the nodes represent the deformation of the object. The edges and clusters colours indicate node connectivity. The markers represent no bending (circle), structured bending (triangle up), unstructured bending (triangle down), and both structured and unstructured bending (square). Note that all graphs are complete graphs but only one edge is shown for clarity.

5.3. Evaluation of the Taxonomy

This section provides an analysis of the capability the taxonomies have to classify the entire set of actions depicted in Table A.2. Given the diverse range of deformations within the action set, taxonomies that group together manipulation skills producing different deformations may be considered less suitable for classifying deformable object manipulation tasks.

To perform this analysis, we first define action-IDs like the ordered set of tags that describe each action, as appearing in Table A.2. We then create a graph where the nodes correspond to an action-ID and an edge connects two nodes when they have the same code. Figures 6-a, 6-b, 6-c, and 6-d, show clusters of action-ID graphs for T-DOM, T-DOM without the deformation category, Paulius et al. [71] taxonomy, and Bullock et al. [9] taxonomy, respectively. Furthermore, each node shape and colour is associated with a deformation as classified in Table A.2, which helps to identify different deformations that are classified together. The node colours serve to differentiate the combinations of deformations present, while each node shape represents a type of bending deformation: circles for no bending, upward triangles for structured bending, downward triangles for unstructured bending, and squares for both types.

The cluster results in Figure 6-a show that our taxonomy can clearly separate actions that generate different deformations, highlighting its capability to categorise disjoint actions by the object deformation involved. This classification results in only four clusters with more than one action-ID, each sharing motion type, interactions and object deformation tags. For instance, the edge between action-IDs "T1-6 slide (out)" and "T2-2 slide (under)" originates from the same structured bending deformation of the towel in task 2 (transport towel) as the end of task 1 (fold towel).

To assess the role of the deformation category in distinguishing between actions, we conducted an ablation study by removing the deformation category and re-clustering the action-IDs, as shown in Figure 6-b. Without the deformation category, a large cluster of eight "grasp (dual)" actions appears. Additionally, two smaller clusters appear involving "grasp" and "grasp (dual)" actions. This indicates that the grasp actions are the same except for the deformation of the grasped object. This deformation is relevant for decision making in tasks like grasping a folded object, where the control strategy needs to retain the object state. In particular, some grasps are separated due to the non-prehensile environment interactions. For instance, the "T9-3: grasp" action is a pinch grasp where the grasped object (glove) is in contact with a rigid object (box) and soft object (glove underneath). Similarly, the "T10-1: grasp" action is performed in the air, that is, without an environment contact with the table as seen in other grasps across the dataset. The impact of the structured and unstructured bending is also clear: actions exhibiting different bending deformations are grouped together, such as the slide actions T1-2, T1-6, T2-2 and T5-2, or the approach actions T1-1, T2-1, T5-1 and T6-1. As previously discussed, such a distinction is relevant for the control strategy. For example, ignoring the deformation when sliding under a folded object might lead to undesired unfolding. Overall, these results highlight the importance of the deformation information to classify semantically the manipulation actions.

Next, we evaluated the taxonomy proposed by Paulius et al. [71], presented in Figure 6-c. This taxonomy produces 22 clusters, with the largest containing 17 action-IDs, primarily from diverse grasping actions, where quite varied deformations are grouped together. Although this taxonomy accounts for deformable objects, it simplifies deformation into the categories of temporal or permanent deformation. This approach is effective for classifying actions that result in a permanent deformation, but does not explicitly address manipulation skills that operate within an object's stress-strain elastic region. Consequently, actions that compress, stretch, twist or bend an object might be grouped together given the motion and interactions with the environment that generate the deformation are the same. This reflects the objective of the taxonomy, which was to classify manipulation from a robot motion perspective, rather than classifying the different types of deformation that take place throughout a manipulation task, as in T-DOM. In addition, the taxonomy does not explicitly classify prehensile grasps, which limits its ability to distinguish manipulations that involve different contact points. Altogether, this makes the taxonomy less suited for classifying the large repertoire of skills required for the robotic manipulation of deformable objects.

Finally, we examine the results from the taxonomy proposed by Bullock et al. [9], shown in Figure 6-d. This taxonomy creates a total of 21 clusters. Although lower than those using Paulius et al. [71] taxonomy, it provides more granularity by classifying prehensile and non-prehensile motions, contacts within the hand, and motion at contact. This is reflected by a smaller largest cluster of 10 action-IDs (compared to the 17 action-IDs in Figure 6-c). This cluster of "grasp" actions resembles that appearing in our taxonomy without deformation in Figure 6-b. Similarly, actions such as lifting, transporting, and folding are grouped together because deformation is not considered. As previously mentioned, the deformation information is relevant because it imposes constraints to the possible motions, and therefore, the planning of actions. In

addition, Bullock's taxonomy does not consider environment contacts, which are important in tasks like placing. This omission explains why placing actions are grouped together with transport, lifts and folds in Bullock's taxonomy, while they are separated in Figure 6-b. These passive contacts with the environment are relevant in rigid manipulation to generate external forces, which are implicitly addressed in Bullock's taxonomy in categories 5 and 7, where passive motion at contact occurs due to an external force. However, these contacts are even more crucial for deformable objects such as clothes, where they act as a third agent that shapes the geometry of the object [7]. Hence, by adding the category *non-prehensile environment* we can treat the environment as an additional gripper within the system, which is relevant in both high- and low-level planning

It is important to note that through our analysis, we are not suggesting that the baseline taxonomies are incorrect. These taxonomies were developed with different objectives in mind. Our aim is to point out that these are missing semantic tags relevant for the robotic manipulation of deformable objects, which are incorporated in our proposed taxonomy.

6. Discussion & Applications

This section discusses observations and limitations of the proposed T-DOM taxonomy, as well as future directions and potential applications of the taxonomy to key aspects of deformable object manipulation.

6.1. Extending Deformation Categories

The proposed taxonomy provides a categorisation of the deformations that can arise when manipulating deformable objects. As discussed in Section 3.1 and Section 4.1, deformations such as tearing and cutting, although rooted in the same fundamental deformation types covered in the taxonomy, lead to permanent deformation of an object. These deformations involve the irreversible breaking of material bonds, making them significantly more difficult to identify and control compared to deformations like bending or stretching.

The study of such permanent deformations is in its early stages, but there are ongoing efforts to address these complex deformation types [37, 44, 97]. Future advances in the identification and control of these deformations will enable enhancing the proposed taxonomy to integrate these failure modes, extending the taxonomy applicability to a broader range of tasks.

6.2. Measuring Deformation

The presented categories for deformation have been given different levels of attention in literature depending on the type of objects. For volumetric, mostly compression is studied. In contrast, for 1D ad 2D deformable objects most attention is put on bending. Indeed, there are several efforts to accurately measure the bending deformation of an object [79], which is critical in the precise manipulation of deformable objects [57]. One example of these efforts is the derivative of the Gauss Linking Integral [19], which can provide a low-dimensional topological representation of cloth state that allows the classification of different bending classes only by distance. While other types of deformation such as tension and shear have been less extensively explored in cloth manipulation, these are highly relevant for planning the control strategies.

At the moment, there is no consensus regarding the sensing and representation of deformation. Our taxonomy aims to pave the way for categorising deformable object manipulation, which could be integrated with techniques that can simultaneously measure deformation and force to plan manipulation.

6.3. Action Segmentation

While the action segmentation performed in Section 5 is currently human-annotated based on observable transitions of deformation, interactions, and contact states, we recognise that ambiguity exists in borderline cases, such as tasks where there is partial observability of the gripper contact or the object deformation, e.g. grasping a glove from a box in task 9. One potential solution to identify such cases is to incorporate additional sensing information, such as tactile sensing. This could enable the identification of grasping

points or detailed deformation. Some examples include tactile-based cloth unfolding [74] and visuo-tactile deformation estimation [66].

Future work could explore combining visuo-tactile information with the proposed taxonomy categories for action and skill recognition [30, 55].

6.4. Assisted Gripper Design

The process of gripper design requires expertise in multiple domains, as well as significant efforts involving the refinement of the design [3]. Manipulation taxonomies such as [9] have influenced several gripper designs [75, 108]. These taxonomies can assist by providing a structured framework to analyse the gripper manipulation modes. As an example, this can enable engineers to tailor specific features that effectively perform manipulation tasks, such as in-hand manipulation [96]. Here, T-DOM can further aid researchers in devising grippers that specialise in deformable object manipulation tasks, such as grippers designed for textile manipulation [39].

To overcome the arduous task of hand-engineering gripper designs for a specific task, co-design algorithms emerged as an alternative to alleviate such human efforts [15, 24, 49]. These approaches have largely focused on rigid object manipulation, leaving designs for deformable object manipulation under-explored due to the complex nature of deformable objects and their interactions. T-DOM offers a structured framework to potentially bridge this gap, facilitating robot design tailored to deformable objects. For instance, retrieving a pancake from a pan highlights the importance of deformation constraints, where in order to preserve the pancake's integrity prehensile grasps need to be avoided, as this would risk destroying the object. Instead, strategies such as contact sliding beneath the pancake and non-prehensile interactions over a wide contact area are preferred [5].

By systematically applying T-DOM subcategories to define task-specific criteria, either for hand-engineered or co-design algorithms, the morphology of a gripper can be adapted to achieve the desired manipulation goals.

6.5. Towards General Manipulation Skills

Finally, in deformable object manipulation, policies are often designed for specific tasks [29, 52, 106], limiting their broader applicability. However, many manipulation actions are shared across different tasks. As shown in our experiments, T-DOM can identify these shared actions, enhancing policy generalisation. For instance, tasks with the same taxonomy tag may involve similar actions, allowing a policy trained on one task to be adapted to another. This identification can improve the efficiency and versatility of robotic systems, reduce the need for retraining, and enable quicker adaptation to new tasks.

Despite the recent advances in language models for manipulating both rigid and deformable objects [13, 48, 70], most of these approaches neglect the deformation information of the object. In this context, the identification of shared actions and different deformations using T-DOM could facilitate learning multi-task policies for complex deformable object manipulation tasks.

7. Conclusion

This work introduced the Taxonomy for Deformable Object Manipulation (T-DOM), aimed to classify the skills required to perform robotic manipulation of deformable objects. The taxonomy focuses on three crucial components: robot motion, the interactions of an object with the robot end-effector or the environment, and, most importantly, object deformation. Key to this taxonomy is a deformation classification that draws from mechanical engineering concepts to categorise deformation via compression, tension, bending, torsion, and shear. Here, we discussed the challenges of identifying different bending deformations, and, to circumvent such challenge, proposed qualitative metrics to classify the existence of complex creasing as structured and unstructured bending, respectively. Then, we introduced a classification for robot motion from a dynamics and energy perspective, integrating quasi-static and dynamic manipulation. Next, for interaction types, we defined prehensile grasps based on the contact constraint geometry, non-prehensile

interactions to distinguish between the environment and agent interactions, and included the special case of contact sliding, also referred to as motion at contact.

To evaluate the taxonomy's effectiveness in characterising deformable object manipulation, we curated a dataset of tasks involving various deformable objects such as cloths, meat-like silicone, and surgical aprons and gloves. We applied T-DOM to classify the task manipulation transitions, representing the actions as action-IDs inspired by prior taxonomies. Our analysis demonstrated that classifying the type of deformation is essential for identifying similar robot actions performed on different deformable objects, where the proposed taxonomy offers a comprehensive framework for classifying the manipulation strategies required to accomplish a wide range of tasks.

Finally, we discussed potential applications and research directions of the proposed taxonomy, connecting the discussed types of deformation with methods for accurately measuring deformation, and providing a generic view into general manipulation policies. All in all, we believe T-DOM lays a solid foundation for advancing the understanding and development of deformable object manipulation.

CRediT authorship contribution statement

David Blanco-Mulero: Conceptualisation, Data curation, Formal analysis, Investigation, Methodology, Project administration, Software, Supervision, Visualization, Writing – original draft. **Yifei Dong**: Conceptualisation, Formal analysis, Software, Validation, Visualization, Writing – original draft. **Julia Borras**: Conceptualisation, Funding acquisition, Validation, Visualization, Writing – original draft. **Florian Pokorny**: Conceptualisation, Funding acquisition, Writing – review & editing. **Carme Torras**: Conceptualisation, Funding acquisition, Resources, Writing – review & editing.

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Appendix A. Dataset Taxonomy Tags.

See Table A.2.

Table A.2: Taxonomy tags describing the ten manipulation tasks and the associated transitions using T-DOM according to Figure 3. The tags are divided into: left and right motion (Motion), left and right prehensile grasp (Grasp), non-prehensile environment interaction (N-P. Env.), left and right non-prehensile active contact interaction (N-P. Act.), environment, left and right contact sliding (CS), deformation (Def.), structured bending (S) and unstructured bending (US).

Task	Action	Motion	Grasp	N-P. Env.	N-P. Act.	CS	Def.	S	US
Fold towel	1-1: approach	G N	N N	R	N N	N N N	N	L1	N
	1-2: slide(under)	G N	N N	R	R N	N A N	N	L1	N
	1-3: grasp	N N	P N	R	N N	N N N	C	L1	N
	1-4: fold	GE N	P N	R	N N	N N N	C	L2	N
	1-5: ungrasp	N N	N N	R	R N	N N N	N	L2	N
	1-6: slide(out)	G N	N N	R	R N	N A N	N	L2	N
Transport towel	2-1: approach	G N	N N	R	N N	N N N	N	L2	N
	2-2: slide(under)	G N	N N	R	R N	N A N	N	L2	N
	2-3: grasp	N N	P N	R	N N	N N N	C	L2	N
	2-4: transport	G N	P N	N	N N	N N N	C	L2	N
	2-5: place	GE N	P N	S	N N	N N N	C	L2	N
	2-6: ungrasp	N N	N N	S	R N	N N N	N	L2	N
	2-7: slide(out)	G N	N N	S	R N	N A N	N	L2	N
Wring out towel	3-1: approach(dual)	G G	N N	R	N N	N N N	N	N	N
	3-2: slide(under-dual)	G G	N N	R	R R	N A A	N	N	N
	3-3: grasp(dual)	N N	P P	R	N N	N N N	N	N	N
	3-4: lift(dual)	G G	P P	N	N N	N N N	TN	L0	N
	3-5: twist(dual)	GE GE	P P	N	N N	N N N	TN+TR	N	N
Edge tracing	4-1: grasp(dual)	N N	P P	R	N N	N N N	N	N	L2
	4-2: tracing(static)	GE N	P P	R	N N	N N P	TN	L0	L2
	4-3: tracing(motion)	N GE	P P	R	N N	N N A	TN	L0	L1
Transport meat	5-1: approach	G N	N N	R	N N	N N N	N	N	N
	5-2: slide(under)	G N	N N	R	R N	N A N	N	N	N
	5-3: grasp	N N	P N	R	N N	N N N	C	N	N
	5-4: transport	G N	P N	N	N N	N N N	C	L0	N
	5-5: place	G N	P N	R	N N	N N N	C	N	N
	5-6: ungrasp	N N	N N	R	R N	N N N	N	N	N
	5-7: slide(out)	N N	N N	R	R N	N A N	N	N	N
Flatten cloth	6-1: approach	G N	N N	R	N N	N N N	N	N	L2
	6-2: grasp	N N	P N	R	N N	N N N	N	N	L2
	6-3: lift	G N	P N	R	N N	N N N	N	N	L2
	6-4: place	G N	P N	R	N N	N N N	N	L1	L1
	6-5: slide(out)	N N	N N	R	R N	N A N	N	L1	L1
Unfold gown	7-1: grasp(dual)	N N	P P	N	N N	N N N	N	N	L2
	7-2: unfold(dynamic)	K K	P P	N	N N	N N N	N	N	L1
Bag opening	8-1: grasp(dual)	N N	P P	N	N N	N N N	N	N	L0
	8-2: unfold(dynamic)	K K	P P	N	N N	N N N	N	N	L0
	8-3: grasp(dual)	N N	P P	N	N N	N N N	N	N	N
	8-4: offer	N N	P P	R	N N	N N N	N	N	N

(continued on next page)

Table A.2 (continued).

Task	Action	Motion		Grasp		N-P. Env.	Act.	CS			Def.	S	US
Open glove	9-1: approach	N	G	N	N	RS	N N	N	N	N	N	N	L1
	9-2: contact	N	G	N	N	RS	N R	N	N	N	N	N	L1
	9-3: grasp	N	N	N	P	RS	N R	N	N	N	TN	N	L1
	9-4: lift	N	G	N	P	N	N N	N	N	N	N	N	L1
	9-5: approach(second)	G	N	N	P	N	N N	N	N	N	N	N	L1
	9-6: grasp(dual)	N	N	P	P	N	N N	N	N	N	N	N	L1
	9-7: ungrasp(second)	N	N	P	N	N	N N	N	N	N	N	N	L0
	9-8: approach(second)	N	G	P	N	N	N N	N	N	N	N	N	L0
	9-9: grasp(dual)	N	N	P	P	N	N N	N	N	N	N	N	L0
	9-10: open	GE	GE	P	P	N	N N	N	N	N	TN	L0	N
Cable looping	10-1: grasp	N	N	N	P	N	N N	N	N	N	N	L0	N
	10-2: hang	N	GE	N	P	N	N N	N	N	N	N	L0	N
	10-3: grasp(dual)	N	N	P	P	N	N N	N	N	N	N	L0	N
	10-4: ungrasp(second)	N	N	P	N	N	N N	N	N	N	N	L0	N
	10-5: approach(second)	G	G	P	N	N	N N	N	N	N	N	L0	N
	10-6: grasp(dual)	N	N	P	P	N	N N	N	N	N	N	L0	N
	10-7: fold(cable)	GE	GE	P	P	N	N N	N	N	N	N	L1	N
	10-8: ungrasp(hold)	N	N	N	P	N	R N	N	N	N	N	L1	N
	10-9: hang	N	GE	N	P	N	R N	N	N	N	N	L1	N
	10-10: grasp(dual)	N	N	P	P	N	N N	N	N	N	N	L1	N
	10-11: ungrasp(second)	N	N	P	N	N	N N	N	N	N	N	L1	N

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