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Household Clothing Set and Benchmarks for Characterising End-Effector Cloth Manipulation

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***Abstract*— The highly varied and deformable structure of clothing presents a challenging task in the area of robot manipulation. Recent literature has shown an increasing interest in this field, however limited information exists on the influence of end-effector selection, instead focusing on the perception, modelling, and methodology in handling fabrics. Here, we present a benchmark set of household clothing items, along with a framework for defining textile features in relation to how the objects can be grasped and manipulated. Alongside these, we present four example benchmarks for evaluating the performance of a robot end-effector in relation to the grasping and manipulation of common pieces of clothing: Edge drag accuracy, edge grasp resilience, grasp encapsulation, and grasp fold generation. We perform these benchmarks on several common robot end-effectors (Franka Emika (FE) Hand with standard and Fin Ray® style fingers (Flex), Robotiq 2F-140, and the Openhand Model T42) and present and discuss their respective performances. Results show that the Robotiq scored highest across most benchmarks, closely followed by the FE hand. The T42 showed excellent encapsulation of items, while the FE (Flex) was particularly successful picking up flat edges.**

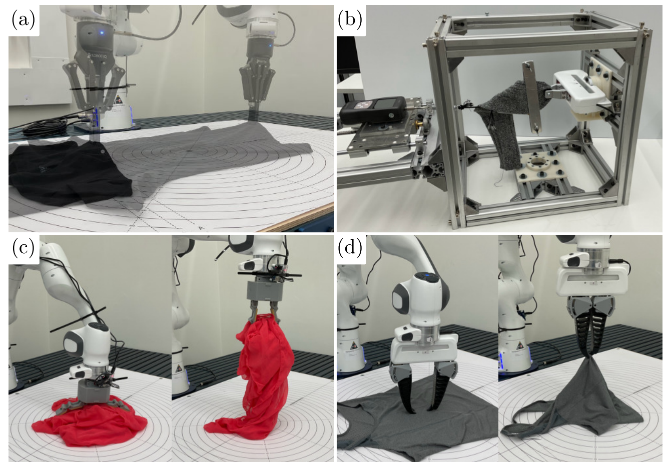

Fig. 1. The four proposed benchmarks: **(a)** Flat edge grasp success and drag placement accuracy, **(b)** edge grasp resilience, **(c)** crumpled object grasp encapsulation, and **(d)** flat non-boundary grasp success.

I. INTRODUCTION

Robotic manipulation of everyday household items has typically focused on rigid objects as non-rigid objects present a variety of challenges. Of non-rigid items, household textiles such as clothing are challenging to grasp, segment, and to model due to their complex changing structure [1], [2]. Robotic manipulation of such items is becoming more important as assisted living and service robots become commercially viable and more adopted [3], [4]. Manipulation tasks such as folding laundry, sorting clothing, or making a bed often require classification, segmentation, and advanced parametric models [5]. However, for these tasks to be achieved a robust grasp is fundamental. This is especially the case for tasks imposing significant forces on clothing items, such as folding clothes using two arms (bimanual) [6] or unfolding by dynamically ‘flinging’ clothing [7]. Unfortunately, there is limited research on factors such as the effect of different textile materials, structures, and edge types on grasp success [7], [8]. The ability to successfully grasp a defined edge on an item of clothing, especially when a manipulation may require high forces imposed on the object, could be of benefit to future household robotic applications.

Another factor affecting the grasping success of cloth items is gripper selection. While parallel jaw grippers, such as those made by Robotiq or Franka Emika, are popular high performing end-effectors, grippers designed specifically for cloth manipulation are intended to show improved performance. Donaire et al. proposed a versatile 3 fingered gripper designed for handling folded clothing and folding clothing in the air, all while maintaining general cloth manipulation capability [9]. The use of roller fingertips has also shown success in edge tracing as a method of spreading out fabric [10]. Minor modifications to existing simple parallel grippers have also demonstrated increased capability, such as the combined use of tactile sensing and neural networks to identify the clothing material [11], and for isolating cloth layers in a folded item [12]. Previous research has defined the grasp technique of textile items, such as pinch, clamp, and pin (for impactive grippers) [13], [14], but due to the lack of a consistent evaluation process limited comparison across these grippers has been performed.

Given the cost to develop or purchase a robotic gripper, consistent quantitative comparison of performance will be of wide reaching benefit. Thus, many researchers are turning to creating benchmarks. These benchmarks enable the evaluation of robots at a mechanism, algorithmic, or systems level. System level benchmarks are commonly proposed in the form of competitions where different teams' systems complete on a set list of real world tasks [15], [16], [17]. Algorithmic level benchmarks target the comparison in performance of planning and perception through simulated environments [18], [19], constraints on hardware [20], or accounting for variations in hardware capability [21]. Mech-

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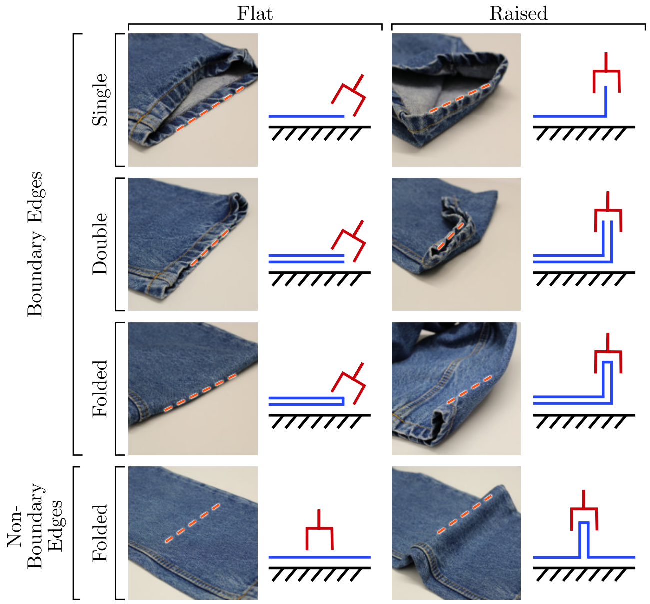

Fig. 2. Proposed classification of textile edge types. Edge types are grouped into boundary (on the physical edge of the clothing) or non-boundary, and raised or laying flat on a surface. Edge types are defined as single, double, and folded. For each edge type, an example is given with the relevant edge highlighted with a dashed orange line, as well as a diagram clearly showing the gripper (**red**), the textile edge (**blue**), and the ground plane (**black**).

Fig. 3. The proposed household clothing object set, with highlighted boundary edge types (single, double, and folded) for each object: **(01)** Sock, **(02)** knickers, **(03)** boxers, **(04)** bra, **(05)** scarf, **(06)** t-shirt, **(07)** vest, **(08)** dress-shirt, **(09)** skirt, **(10)** nightdress, **(11)** jeans, **(12)** hoodie, and **(13)** fleece. The full object details, such as dimensions, elasticity, and material type, are available online at `https://github.com/DysonRobotics/HouseholdClothingBenchmark`.

anism level benchmarks focus in on component performance, these benchmarks usually eliminate or limit the complexity of the algorithms and extra system elements [17], [22].

Benchmarks must be easy to implement and replicate, clear, and reliable in order for them to be widely used. The YCB object set is widely used for manipulation benchmarks, as it is well defined and readily available [23]. While efforts have been made to classify textile objects such as clothing, the wide range of physical and semantic properties make this a considerable challenge [11]. Achieving consistent and representative experimental setups of cloth item states in a benchmark, such as folded or crumpled, is difficult due to the large continuous state space. Garcia-Camacho et al. have expanded the YCB set with cloth-like objects, identifying four specific categories. Here, they define the first category, household items, focusing on tablecloths, sheets, and linens [24]. This research will focus on their second category of dressing items.

II. SOFT OBJECT CLASSIFICATION

In this section, we propose a classification for the different edge types encountered in textiles, designed to cover all possible edges on an item. They are characterised so that the state of the textile item, such as folded, crumpled, or laid flat, does not affect the classification. We also describe a clothing object set and justify reasons for the selecting the items. Finally, we present a definition of crumpled, and a method for placing a textile item in a crumpled state.

A. Edge Classification

We propose a classification that defines textiles edges based on features that describe the types of grasps that can be performed. The proposed edge classification can be viewed in Fig 2, with both diagrams and examples of each edge on a pair of jeans. The first criterion is to classify whether the edge is raised or flat. A raised edge must be graspable without using a a clamp grasp, where a clamp grasp is defined by any part of the gripper sliding underneath the edge [14]). The second criterion defines whether the edge is a boundary edge or not. We define a boundary as the edges of the object that form when the object is laid flat as a 2D structure.

We define three sub types of boundary edge: single, double and folded. A single edge is the edge of a single layer of fabric. A double edge is two layers of fabric with parallel edges, such as the bottom of a leg of jeans. If the top layer of a double edge is moved away from the bottom edge, then the bottom edge would be classified as a single edge. A folded edge is the same as a double edge, except folded cloth replaces the open space between the sheets. A folded edge is present when one or more sheets of fabric bend over themselves, thereby covering the opening (e.g. the edge along the legs of a pair of jeans).

A non-boundary edge is any edge that does not lie on the 2D boundary of where the cloth touches the surface below. The 'edge' can be a flat piece of fabric or can be a raised ridge (see the bottom row of Fig 2). In the case of a flat piece of fabric, a raised folded edge is formed as the gripper deforms the fabric.

B. Clothing Object Set

In this object set we focus on items of clothing. The clothing object set can be seen in Fig. 3, and the properties of each object are detailed online, following the information criteria previously proposed [24]. Following on from the proposed edge classification, in Fig. 3 the edges of each item of clothing are also highlighted to identify which of the three (single, double, folded) types of edges exist. Non-

TABLE I

RESULTS OF DIAMETER SPREAD FROM THE OBJECT DROP TEST.

Item	Drop Test Average (mm)			Nominal Bounding Diameter (mm)
	Loose	Compressed	% Diff.	
01 Socks	425	430	1 %	400
02 Knickers	375	380	1 %	400
03 Boxers	480	460	4 %	500
04 Bra	450	450	0 %	500
05 Scarf	690	605	14 %	600
06 T-Shirt	700	665	5 %	700
07 Vest	625	550	14 %	600
08 Dress-Shirt	890	885	1 %	900
09 Skirt	705	680	4 %	700
10 Nightdress	755	740	2 %	700
11 Jeans	845	835	1 %	800
12 Hoodie	770	700	6 %	700
13 Flece	840	795	10 %	800

boundary folded edges are not highlighted as they can be selected anywhere there is a flat surface, and raised edges are not shown as the objects are laid flat here.

The object set consists of typical items of clothing and includes both male and female items with a wide diversity of structures, dimensions, weights, and fabrics. We detail the weights and approximate dimensions of each object, and also provide the percentage of elasticity across the height, width, and diagonal of each object and a breakdown of the fabric components. Finally, we assign each object a unique ID for ease of reference, and encourage others to extend the object set should they feel an item of significance is missing.

As highlighted by Garcia-Camacho et al., one of challenges in creating a standardised object set is the continuity of the stock of a particular item [24]. This is especially the case for clothing, where the life cycle of an item is very short. Instead of specifying the exact item to use for the benchmark, we propose it is sufficient to provide general classes of objects and the properties they exhibit. This closely matches the home environment where there is reasonable intra-class variation for an item of clothing but the general properties are still maintained. The lack of hard definition on the object set is a limitation when reproducing and comparing results across publications, but we argue that if the results are so closely tied to a specific instance of a pair of clothing it lacks any useful generalisable outcomes. To allow for intra-class variation, we allow a 5% tolerance for the object dimensions and elasticity, with allowable range detailed in the object set.

C. Defining Crumpled

Previous work has proposed definitions for common clothing states: folded, flat and crumpled. Flat and folded states are possible to specify in a repeatable way due to their inherent ordered structure as laid out in [24]. A reproducible definition for crumpled is harder to specify due to the lack of repeatable structure or order. We performed a set of tests to attempt to identify any repeatable properties that could be used to better constrain the definition of crumpled.

Following initial testing at a variety of heights (50mm steps), a drop height of 750 mm for each item was selected to allow for the clothing to adequately rearrange before settling on the alignment grid. We tested two conditions: cloths held loosely and clothes compressed into a tight ball. For each condition the encircling diameter of the dropped cloth was recorded 5 times and an average is displayed in table I.

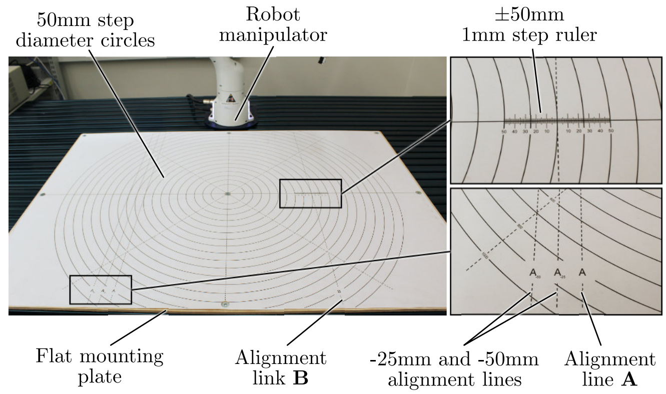

Fig. 4. The A0 alignment grid used for the defined benchmarks, with highlighted components. The grid is available online at https://github.com/DysonRobotics/HouseholdClothingBenchmark

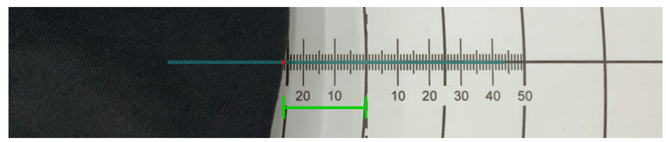

Fig. 5. An example measurement (21 mm) of the placement accuracy of a dragged object, highlighting the location on the object (**red**) along the central line (**blue**) that the offset from line B is measured to (**green**).

The results show that there was $<14\,\%$ difference between the loose and compressed drop conditions. This implies that the method of holding the cloth before dropping does not have a large effect on the resulting distribution of the crumpled state. Therefore all that is required to produce a crumpled state is to drop it from 750 mm. We defined a protocol to normalise the crumpled state to reduce variance between tests. The average value of both drop tests is rounded to the near 100 mm and when an item is dropped any edges that exceed that diameter are pushed into the nominal bounding diameter.

III. SOFT OBJECT GRIPPER BENCHMARK

In this section, we present four benchmarks for assessing the ability of a robotic gripper to grasp and handle the textile edges defined in Fig. 2. For each, we include the setup, required task, and collected metrics. For each benchmark, we recommend 5 repeats for each object being performed and an average taken.

An A0 sized alignment grid, shown in Fig. 4, was designed to be attached to a flat and rigid backing plate with features to aid conducting the benchmarks. The use of these features is explained in the following benchmarks.

A. Flat edge grasp success and drag placement accuracy

This benchmark measures the grasping success with respect to flat boundary edges, and also assesses the placement accuracy when dragging the edge, such as in a folding manipulation. The task of this benchmark is to grasp the flat edge and successfully lift it (+50 mm Z axis) off the surface.

Using the alignment grid, the current edge being evaluated is aligned with alignment line A, with the remainder of the object to the left of the line (overlapping the A_{-25} and A_{-50} lines). When performing the grasp, the grasping location is limited to the available fabric between the A and A_{-25} lines. Next, the item is dragged 500 mm via horizontal translation of the manipulator. Finally, the object is lowered almost to the surface (-40 mm Z axis), and the edge released.

The success of grasp is binary, and is determined by whether the full desired edge is grasped by the gripper (e.g. in the case of the double edge, only a single layer being grasped is measured as a fail), and if the edge is held throughout the motion of the arm. If the object is dropped at any point other than the release motion, this is also recorded as a failure. Once dragged, the placement accuracy of the object edge is also evaluated. This is performed from alignment line B using the 1 mm step ruler to the resulting location of the instantaneous point along the dragged edge that resides on the given ruler. An example of this measurement is shown in Fig. 5. For a perfect score, the edge is successfully grasped, held throughout the motion, and is placed exactly on alignment line B (an offset of 0 mm).

For this benchmark, we suggest evaluating only clothing items that would require folding, such as those with significant dimensions. Therefore, we do not include the socks, knickers, boxers, or bra in this benchmark.

B. Edge grasp resilience

For this benchmark, we evaluate the payload capacity of single, double, and folded edges. This can be seen as the best-case payload performance for both flat and raised edges following a grasp, for both boundary and non-boundary edges. To evaluate the payload performance, we allow a gripper to grasp the required edge of the object up to a maximum depth of 25 mm. Either the gripper or object must be fixed to a rigid platform, while the other is then moved linearly away, measuring the maximum resisting force (using a load cell or similar) provided by the gripper before the grasp fails. A grasp failure is identified as the onset of major slip, which is clearly identified following a significant drop in force. The maximum resisting force is therefore the peak before this drop occurs. If a grasp does not fail, we cap the maximum imposed force at 30 N, as this is significantly above the weight of any item of clothing, and from our experiments limits damage to the items. As the worst-case edge grasp payload occurs when the clothing object is fully lifted off a surface and accelerated upwards, we suggest only the heavier objects are evaluated in this experiment. Using a minimum mass of 0.1 kg, this results in the clothing items t-shirt, dress-shirt, jeans, hoodie, and fleece being evaluated. The gripper was placed on a fixed platform, and the objects were attached to a load cell on a motorised linear rail. The experimental setup can be seen in Fig. 6.

C. Crumpled object grasp encapsulation

In the third benchmark, we focus on the ability to grasp the entire object, rather than a single edge. From the perspective

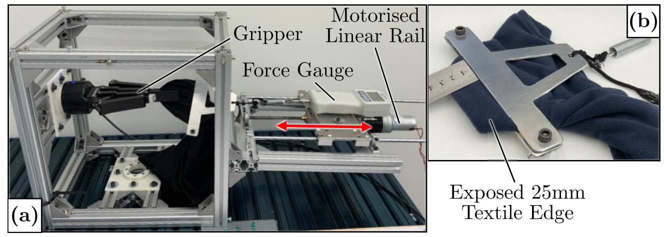

Fig. 6. The grasp resilience experimental setup: **(a)** The overall experimental setup, highlighting the experiment components and direction of motion of the linear rail (**red**), and **(b)** an enlarged image of the clamping system used to expose a desired edge of the textile.

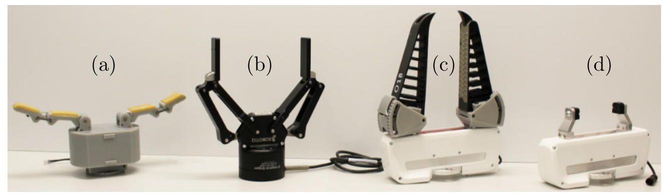

Fig. 7. The grippers evaluated: **(a)** OpenHand Model T42 (pivot-flex configuration), **(b)** Robotiq 2F-140 (non-adaptive mode), **(c)** FE Hand with custom Fin Ray® style fingers, and **(d)** FE Hand.

of household robotics, this is a relevant benchmark for tasks that require the manipulation of objects outside of the workspace of a manipulator, therefore requiring some form of locomotion. To prevent the clothing item from catching on other items or having unwanted interaction with the locomotion system, in an ideal case the entire clothing object is encapsulated by the gripper, with no object components (such as sleeves) touching the floor.

The clothing object is placed in a crumpled state in the centre of the grid using the method described in section II-C. The gripper is then allowed to grasp anywhere on the item, with the 'optimal' location selected by the operator. Following a grasp, the gripper is raised in 100 mm increments, up to a maximum of 500 mm. The first height that results in the clothing object completely leaving the alignment grid surface is recorded. If the object is dropped at any point during this manipulation, a failure is recorded. Alternatively, if the manipulator reaches the full offset of 500 mm and the object has not left the surface, an alternative mark 'M' is given (representing 'maximum reached'). This is repeated for both full and half crumpled diameters, simulating a typical crumpled state as well as a crumpled state following a simple manipulation to achieve a compressed state. In this benchmark, all items in the object set are used.

D. Flat non-boundary grasp success

The final benchmark focuses solely on the flat, non-boundary folded edge, and evaluates a grippers ability to grasp a flat, featureless layer of fabric. This is relevant for grasping cases where the clothing object is laid flat and a central grasp is desired. As the quantitative performance of payload is already addressed in benchmark B, only a binary success/fail score is measured.

Using the alignment grid with manipulator and gripper, the clothing object is laid on the grid. The grid is marked with

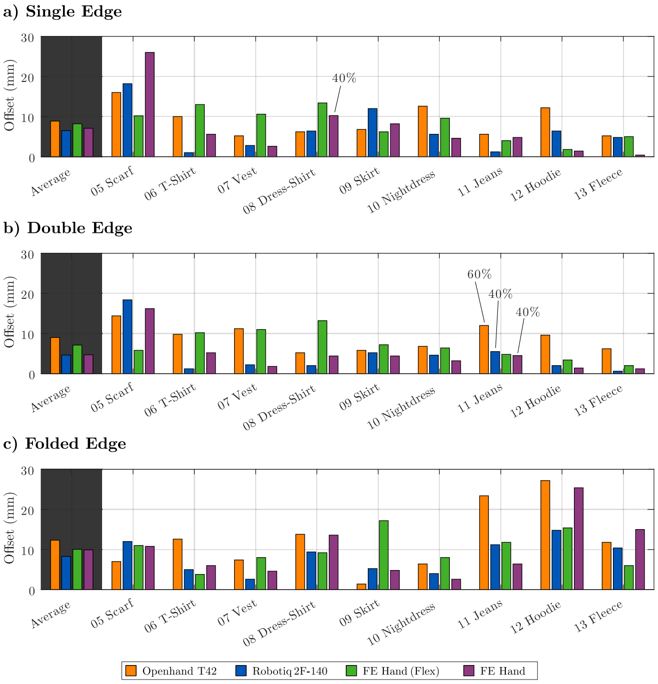

Fig. 8. Results from Benchmark A: Flat edge grasp success and drag placement accuracy. The average offset in placement accuracy for each item is shown, as well as the overall average for all items for each edge type: **(a)** Single edge, **(b)** double edge, and **(c)** folded edge. The success rate for any object that did not achieve 100 % success rate is also shown.

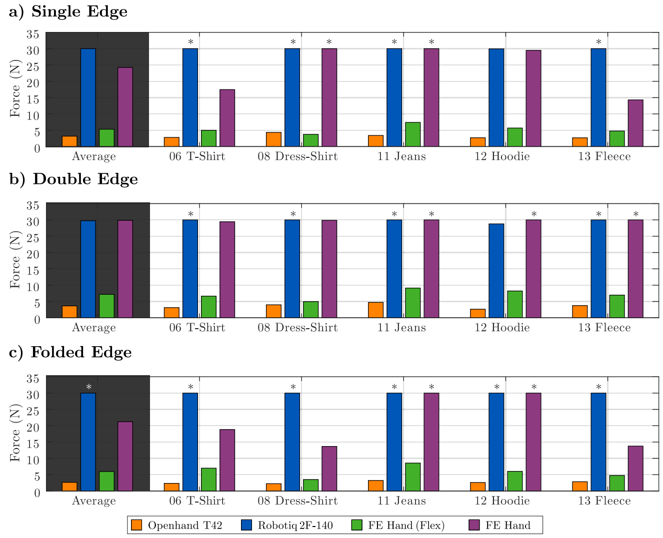

Fig. 9. Results from Benchmark B: Edge grasp payload. The average payload for each item is shown, as well as the overall average for all items for each edge type: **(a)** Single edge, **(b)** double edge, and **(c)** folded edge. Objects that achieved the maximum score of 30N (i.e. no failure) are highlighted with a *****.

50 mm step increasing diameter circles, and the fabric should be configured such that a featureless, flat layer of fabric is located within the 100 mm diameter circle. The gripper should then perform a grasp of the object at the centre of the grid, followed by a translation of 100 mm vertically. This is held for 5 s, after which a success score is given. Should the gripper fail to grasp the item, lift it off the surface, or drop it during the 5 s period, a fail score is instead given. As per benchmark C, all clothing objects are relevant here.

IV. EVALUATION

Using the proposed benchmarks, we evaluate four common types of parallel grippers, shown in Fig. 7:

- The OpenHand Model T42, a popular open source underactuated gripper [25].
- The Franka Emika (FE) Hand, a two fingered parallel gripper that accompanies the FE Panda Manipulator, a common cobot used in research.
- A custom hand using Fin Ray® style flexible adaptive fingers mounted to the FE Hand base [26]. This gripper is herein called 'FE Hand (Flex)' for simplicity.
- The Robotiq 2F-140 gripper, a 4-bar linkage based adaptive gripper that is popular in industry, here used in non-adaptive pinch mode.

While only 2-fingered grippers were evaluated here due to their popularity in precision grasping, it is worth noting that the benchmarks are not limited to a specific hand design, and future research will ideally benchmark alternative designs. Each of the grippers is used with the FE Panda Manipulator, with the exception of benchmark B (payload) where the gripper is mounted in the experimental setup rig. Each benchmark was carried out according to their respective descriptions. The results for each of the benchmarks can be seen in Fig. 8, Fig. 9, Fig. 10, and Fig. 11, respectively.

V. DISCUSSION

In this section we discuss the experimental results of our benchmark for the selected grippers.

Benchmark A: The Robotiq had the best overall average performance (6.5 mm offset), followed by the FE Hand (7.2 mm), FE Hand (Flex) (8.5 mm), and the Openhand T42 (10.1 mm). This order holds true for all edge types. We attribute this to the high force high friction grasp of the Robotiq. With regards to reliability, only the FE Hand (Flex) did not fail any grasps. It was the only gripper to successfully grasp the double edge jeans, where the thickness of the edge and the weight of the jeans proved to be difficult for the grippers without a nail for getting under the edge.

Benchmark B: The results are shown in Fig. 9, where the Robotiq almost achieved the maximum score for this benchmark. The high force and high friction of the Robotiq meant that it was able to maintain a strong grasp on all the objects, the exception being high elasticity objects. The FE hand also had a high score. It may be particularly suited to the double edge grasp due to the geometry of the fingers, which could catch the hem. We can see that for folded edge the score is lower, presumably due to the lack of hem for this edge type. The FE (Flex) was limited by low grasp forces due to the low stiffness fingers. However, it still managed to achieve a force above the weight of all the items, where the T42 did not.

Benchmark C: From Fig. 10, the grasp success rate showed limited difference between crumpled and compressed

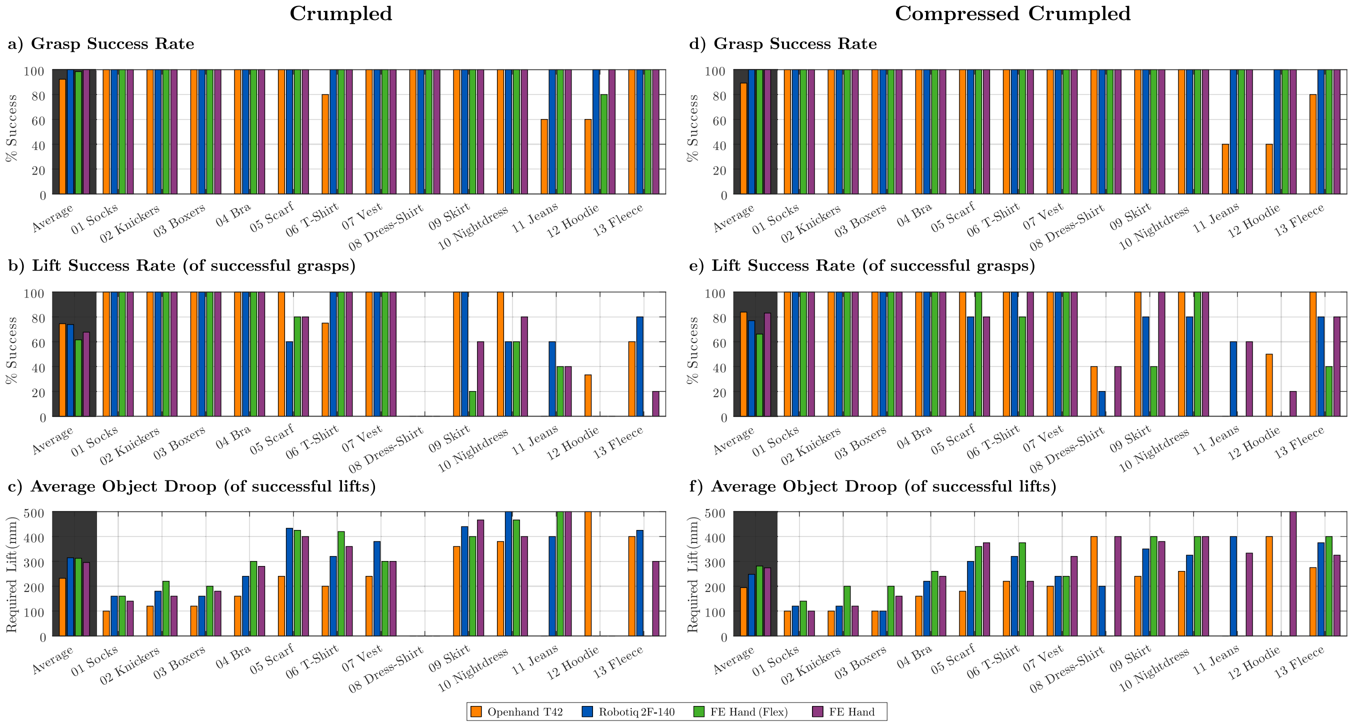

Fig. 10. Results from Benchmark C: Crumpled object grasp encapsulation. The average grasp success rate, lift success rate, and droop for each item is shown, as well as the overall average for all items. Objects were evaluated as crumpled (**a**), (**b**), (**c**)) and compressed (**d**), (**e**), (**f**)).

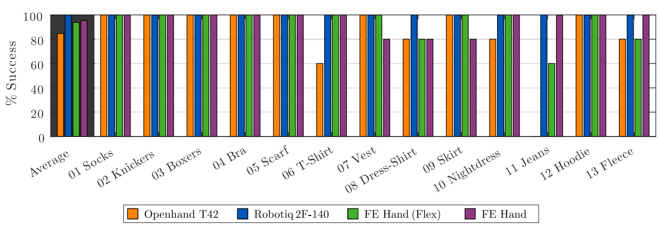

Fig. 11. Results from Benchmark D: Flat non-boundary grasp success. The average successful grasp rate for each item is shown, as well as the overall average for all items.

clothing states. Compressed items showed a higher lift success rate (+8 %) compared to crumpled, possibly due to improved enveloping by the grippers. Overall, average droop for compressed items was 249 mm. The dress shirt proved to be the most challenging item, particularly in its non-compressed state. Items with long sleeves or legs, such as jeans and hoodie, showed a similar lift failure rate, due to not being encapsulated. Small items were all successfully lifted off the surface with a droop of less than 300 mm.

Both the Robotiq and FE grippers had a 100 % grasp rate, however the Robotiq had many more 'max' measurements, indicating poor encapsulation. The T42 had the highest lift success rate (80 %) and lowest object droop (211 mm), however it had the lowest grasp success rate (91 %). The FE (Flex) hand's small span made it more difficult to encapsulate the objects, giving it the lowest score in lift success (64 %).

Benchmark D: Fig. 11 shows The FE and FE (Flex) achieved similar scores, with the FE gripper performing better on the jeans and fleece, while the FE (Flex) was superior on the vest and skirt. This difference may be due to the FE (Flex) lacking the finger stiffness required to grasp a thicker material object, while the fingernail feature enabled a better grasp on lightweight items. The Robotiq successfully grasped all items, thanks to the closing motion of the four-bar linkage gripper, where the high friction fingertips are pushed into the material during the grasp action. The T42 had the lowest score, failing to grasp the jeans and only scoring 60 % on the T-shirt, possibly due to the friction of it's fingers not being sufficient to drag the material of heavier objects.

VI. CONCLUSIONS

In this paper we presented a clothing object set for benchmarking, focusing on typical household clothing items. Additionally, we proposed a novel classification for textile edges, taking into account the current state of the object geometry, along with a defined method for consistently achieving a crumpled object state. Using the object set, we designed four benchmarks for assessing the performance of grippers in relation to the defined textile edge classification, namely flat edge grasp success and drag placement accuracy, edge grasp resilience, crumpled object grasp encapsulation, and flat non-boundary grasp success. We then evaluated four common parallel grippers through these benchmarks, resulting in a variety of learning discussed. We found that each of the tested grippers relative performance varied across the tests. The T42 proved to have the strongest encapsulation performance and the FE (flex) was the most effective at successfully grasping flat edges. Overall, the Robotiq was the strongest across all of the benchmarks, closely followed by the FE hand.

REFERENCES

[1] Y. C. Hou, K. S. M. Sahari, and D. N. T. How, "A review on modeling of flexible deformable object for dexterous robotic manipulation," *International Journal of Advanced Robotic Systems*, vol. 16, no. 3, p. 1729881419848894, 2019.

[2] P. Jiménez and C. Torras, "Perception of cloth in assistive robotic manipulation tasks," *Natural Computing*, vol. 19, no. 2, pp. 409–431, 2020.

[3] A. H. Sapci and H. A. Sapci, "Innovative assisted living tools, remote monitoring technologies, artificial intelligence-driven solutions, and robotic systems for aging societies: systematic review," *JMIR aging*, vol. 2, no. 2, p. e15429, 2019.

[4] S. S. Park, C. D. Tung, and H. Lee, "The adoption of ai service robots: A comparison between credence and experience service settings," *Psychology & Marketing*, vol. 38, no. 4, pp. 691–703, 2021.

[5] G. Alenyà Ribas, A. Ramisa Ayats, F. Moreno-Noguer, and C. Torras, "Characterization of textile grasping experiments," in *Proceedings of the 2012 ICRA Workshop on Conditions for Replicable Experiments and Performance Comparison in Robotics Research*, 2012, pp. 1–6.

[6] I. Garcia-Camacho, M. Lippi, M. C. Welle, H. Yin, R. Antonova, A. Varava, J. Borras, C. Torras, A. Marino, G. Alenya, *et al.*, "Benchmarking bimanual cloth manipulation," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 1111–1118, 2020.

[7] H. Ha and S. Song, "Flingbot: The unreasonable effectiveness of dynamic manipulation for cloth unfolding," in *Conference on Robot Learning*. PMLR, 2022, pp. 24–33.

[8] S. Miller, J. Van Den Berg, M. Fritz, T. Darrell, K. Goldberg, and P. Abbeel, "A geometric approach to robotic laundry folding," *The International Journal of Robotics Research*, vol. 31, no. 2, pp. 249–267, 2012.

[9] S. Donaire, J. Borras, G. Alenya, and C. Torras, "A versatile gripper for cloth manipulation," *IEEE Robotics and Automation Letters*, vol. 5, no. 4, pp. 6520–6527, 2020.

[10] K. S. M. Sahari, H. Seki, Y. Kamiya, and M. Hikizu, "Clothes manipulation by robot grippers with roller fingertips," *Advanced Robotics*, vol. 24, no. 1-2, pp. 139–158, 2010.

[11] W. Yuan, Y. Mo, S. Wang, and E. H. Adelson, "Active clothing material perception using tactile sensing and deep learning," in *2018 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2018, pp. 4842–4849.

[12] S. Tirumala, T. Weng, D. Seita, O. Kroemer, Z. Temel, and D. Held, "Learning to singulate layers of cloth using tactile feedback," *arXiv preprint arXiv:2207.11196*, 2022.

[13] V. C. Moulianitis, A. J. Dentsoras, and N. A. Aspragathos, "A knowledge-based system for the conceptual design of grippers for handling fabrics," *AI EDAM*, vol. 13, no. 1, pp. 13–25, 1999.

[14] P. Jiménez, "Visual grasp point localization, classification and state recognition in robotic manipulation of cloth: An overview," *Robotics and Autonomous Systems*, vol. 92, pp. 107–125, 2017.

[15] F. Amigoni, E. Bastianelli, J. Berghofer, A. Bonarini, G. Fontana, N. Hochgeschwender, L. Iocchi, G. Kraetzschmar, P. Lima, M. Matteucci, *et al.*, "Competitions for benchmarking: Task and functionality scoring complete performance assessment," *IEEE Robotics & Automation Magazine*, vol. 22, no. 3, pp. 53–61, 2015.

[16] Y. Sun, J. Falco, M. A. Roa, and B. Calli, "Research challenges and progress in robotic grasping and manipulation competitions," *IEEE robotics and automation letters*, vol. 7, no. 2, pp. 874–881, 2021.

[17] B. Calli, A. Walsman, A. Singh, S. Srinivasa, P. Abbeel, and A. M. Dollar, "Benchmarking in manipulation research: Using the yale-cmu-berkeley object and model set," *IEEE Robotics & Automation Magazine*, vol. 22, no. 3, pp. 36–52, 2015.

[18] J. Weisz, Y. Huang, F. Lier, S. Sethumadhavan, and P. Allen, "Robobench: Towards sustainable robotics system benchmarking," in *2016 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2016, pp. 3383–3389.

[19] S. Ulbrich, D. Kappler, T. Asfour, N. Vahrenkamp, A. Bierbaum, M. Przybylski, and R. Dillmann, "The opengrasp benchmarking suite: An environment for the comparative analysis of grasping and dexterous manipulation," in *2011 IEEE/RSJ International Conference on Intelligent Robots and Systems*. IEEE, 2011, pp. 1761–1767.

[20] N. Funk, C. Schaff, R. Madan, T. Yoneda, J. U. De Jesus, J. Watson, E. K. Gordon, F. Widmaier, S. Bauer, S. S. Srinivasa, *et al.*, "Benchmarking structured policies and policy optimization for real-world dexterous object manipulation," *IEEE Robotics and Automation Letters*, vol. 7, no. 1, pp. 478–485, 2021.

[21] F. Bottarel, G. Vezzani, U. Pattacini, and L. Natale, "Graspa 1.0: Graspa is a robot arm grasping performance benchmark," *IEEE Robotics and Automation Letters*, vol. 5, no. 2, pp. 836–843, 2020.

[22] J. Falco, K. Van Wyk, S. Liu, and S. Carpin, "Grasping the performance: Facilitating replicable performance measures via benchmarking and standardized methodologies," *IEEE Robotics & Automation Magazine*, vol. 22, no. 4, pp. 125–136, 2015.

[23] B. Calli, A. Singh, A. Walsman, S. Srinivasa, P. Abbeel, and A. M. Dollar, "The ycb object and model set: Towards common benchmarks for manipulation research," in *2015 international conference on advanced robotics (ICAR)*. IEEE, 2015, pp. 510–517.

[24] I. Garcia-Camacho, J. Borràs, B. Calli, A. Norton, and G. Alenyà, "Household cloth object set: Fostering benchmarking in deformable object manipulation," *IEEE Robotics and Automation Letters*, vol. 7, no. 3, pp. 5866–5873, 2022.

[25] R. Ma and A. Dollar, "Yale openhand project: Optimizing open-source hand designs for ease of fabrication and adoption," *IEEE Robotics & Automation Magazine*, vol. 24, no. 1, pp. 32–40, 2017.

[26] O. Pfaff, S. Simeonov, I. Cirovic, P. Stano, *et al.*, "Application of fin ray effect approach for production process automation," *Annals of DAAAM & Proceedings*, vol. 22, no. 1, pp. 1247–1249, 2011.