Using Task Symmetry for Human-Robot Collaborative Manipulation of Deformable Objects Without Modeling Deformation

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I. INTRODUCTION

We present a symmetry-based method that allows humans and robots to collaboratively manipulate deformable objects. The method does not require modeling and simulating deformation. Our method is based on the concept of diminishing rigidity, which we use to quickly compute an approximation to the Jacobian of the deformable object without using simulation. This Jacobian is used to drive the points within the deformable object towards a set of targets. For collaborative tasks, these targets are derived from the human's "side" of the task, i.e. the robot seeks to preserve symmetry of the deformable object as the human is manipulating it. However, this method alone is insufficient to avoid stretching the object beyond its allowed length and to avoid gripper collision with obstacles. Thus a key part of our approach is incorporating techniques to avoid collision and excessive stretching. Our experiments show how to perform a folding task with a two-dimensional deformable object, where the robot and a user simultaneously manipulate the deformable object. Our experiments are conducted in simulation but we emphasize that our method does not have access to the model of the deformable object used by the simulator, although we assume we are able to sense the geometry of the object (though sensing may be noisy). While our method is local (i.e. a controller), we find that it is quite versatile in the range of tasks it can perform, especially since it has no knowledge of the model of the deformable object. Our method can be applied to surgical tasks where the human and robot control separate manipulators to accomplish a common task; for instance for retracting tissue.

The primary challenge of manipulating deformable objects is that they are very difficult to model and simulate. Many models and simulation methods have been proposed [1], [2], [3], [4], [5], [6]. Even if it were possible to obtain a perfect model of the deformable object, simulating that model is time-consuming and often very sensitive to simulation parameters.

Given the difficulties of deformable object modeling and simulation, we seek to explore the practicality of manipulating deformable objects without explicitly modeling and simulating them. Our hypothesis is that model-free deformable manipulation like this can be accomplished by exploiting a property we call *diminishing rigidity* – i.e. that the effect of gripper motion along the deformable object diminishes as the distance from the gripper increases. This property is based on the assumption that the combination of gravity, friction, and stretching of the deformable object dissipate the force applied at the gripper. Of course this property does not hold for all deformable objects in all situations, but we have found it to be effective in many examples [7].

In this poster we address the problem of manipulating deformable objects locally, i.e. given a desired displacement of the points comprising the object we compute a motion of the grippers that achieves that displacement as closely as possible, which is similar to the work in visual servoing of deformable objects [8], [9], [10]. We apply our method to the collaborative task of a human and robot folding a cloth in our experiment.

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II. A LOCAL METHOD FOR DEFORMABLE OBJECT MANIPULATION

Our method works by iteratively moving the points of the object closer to their targets. To do this we use an approximation to the true Jacobian of the deformable object $J(q)$.

Numerically estimating the Jacobian of the deformable object is impractical in our scenario because we do not assume to have access to a fast and accurate simulation. This approach also scales poorly with the number of grippers. Instead, our approximation to $J(q)$, called the *diminishing rigidity Jacobian* $\tilde{J}(q)$, is defined based on the assumption that points closer to the gripper match the gripper's movement more than farther points.

While applying the pseudo-inverse of $\tilde{J}(q)$ will indeed drive the points in the object toward a given target, we also need to take excessive stretching and collision avoidance into account. Excessive stretching is compensated for by introducing a virtual force that pushes points toward each other when their maximum separation is close to being exceeded:

$$\dot{q} = \tilde{J}(q)^{+}(\dot{\mathcal{P}} + \dot{\mathcal{P}}_s) \quad (1)$$

Here $\dot{q}$ is the output velocity of the gripper DOFs (a free-floating rigid body in this work), $\dot{\mathcal{P}}$ is the desired movement of points in the object toward their targets, and $\dot{\mathcal{P}}_s$ is the desired movement of points in the object to compensate for stretching. Equation 2 incorporates the above with collision avoidance:

$$\dot{q}'_g = \gamma_g(J^{+}_{p^g}\dot{x}_{p^g} + (\mathbf{I} - J^{+}_{p^g}J_{p^g})\dot{q}_g) + (1-\gamma_g)\dot{q}_g \quad (2)$$

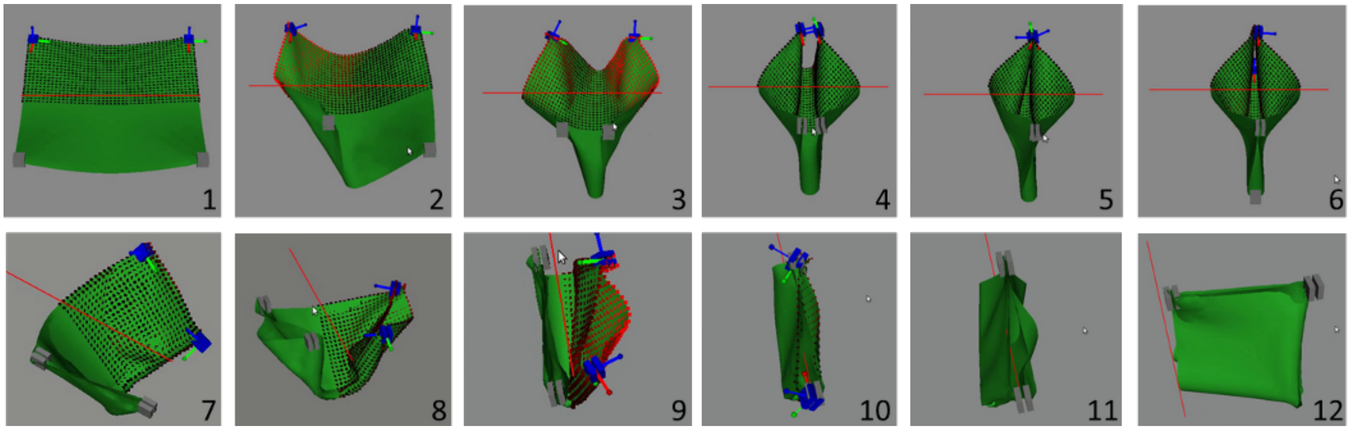

Fig. 1. Sequence of snapshots showing the execution of the cloth folding experiment. The autonomous grippers are blue, and the grippers controlled by the user are gray. The red line marks the plane of symmetry. The points on the autonomous grippers' side of the cloth range from red (distant from the corresponding point on the user's side) to black (close to the corresponding point on the user's side). In frames 1-5 the user brings the gray grippers into alignment for the first re-grasp while the autonomous grippers preserve symmetry for their side of the cloth. As seen in frame 5, the difference between the user's side and the autonomous side is small (the points on autonomous gripper side are black). Frame 6 shows the first re-grasp, where one of the user's grippers re-grasps the top of the cloth while the other grasps the bottom-most part of the cloth. The autonomous grippers perform the same re-grasp on their side. In frames 7-9 the user brings the cloth into alignment for the second re-grasp while the autonomous grippers preserve symmetry. The user then brings the gray grippers to the plane of symmetry so that they overlap with the autonomous grippers (frame 10). The user's grippers re-grasp the cloth in frame 11 and the autonomous grippers are removed. The user displays the folded cloth in frame 12.

Here, $\dot{q}'_g$ is the computed movement of the gth gripper, J_{p^g} is the Jacobian of point p on gripper g w.r.t gripper g, $\dot{q}_g$ is the movement of the gripper that accounts for moving toward the target and excessive stretching (see Equation 1), $\dot{x}_{p^g}$, is a velocity pushing the point p on gripper g away from an obstacle, and γ_g is a scalar that ranges from 0 to 1 depending on the proximity of the closest point on a gripper to an obstacle. See [7] for more information on this method.

A. Human-robot Collaboration

We found that intuitive collaboration between a user and the autonomous grippers controlled by the method above could be accomplished through *symmetry preservation*. We define the targets for the objects' points such that the autonomous grippers attempt to match their side of the object to the user's side of the object. To encode this behavior, we define a plane of symmetry halfway between the user's grippers and the autonomous grippers at their initial configuration (note that this plane is static, it does not move with the object). We also do not assume that the location of the user's grippers are know; we can only perceive the state of the object.

III. RESULTS

In this experiment, a user uses two grippers to collaborate with two autonomous grippers to fold a cloth twice. This task is inspired by the common laundry task of folding a bedsheet (see Figure 1). The user controls his or her grippers using a mouse for translation and keyboard for rotation. The experiment was conducted in the open-source Bullet simulator [11], with additional wrapper code developed at UC Berkeley. The sizes of objects and parameters of the simulator were tuned to produce visually-realistic behavior. We again emphasize that our method has no access to the simulation parameters. Figure 1 shows the successful execution of the collaborative cloth folding task.

To simulate sensor uncertainty we perturbed the position of the points of the object reported by the simulator with zero-mean Gaussian random noise (generated using the Box-Muller method). At the presentation, a video will show execution of the task where the sensor noise has a std. dev. of 2.5cm (the length of the cloth is 10m). While the controller is slower to achieve symmetry in the presence of noise, the folding task can still be performed.

IV. DISCUSSION

In future work we seek to explore methods for automatically-adapt the deformation Jacobian online (perhaps using methods similar to [12]). We believe automatic tuning will allow the Jacobian to adapt quickly to new situations and will diminish the effects of local minima. We also seek to extend our method to three-dimensional deformable objects.

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