Abstract—Previous soft tissue manipulation studies assumed that the grasping point was known and the target deformation can be achieved. During the operation, the constraints are supposed to be constant, and there is no obstacles around the soft tissue. To go beyond these assumptions, a deep reinforcement learning framework with prior knowledge is proposed for soft tissue manipulation under unknown constraints, such as the force applied by fascia. The prior knowledge is represented through an intuitive manipulation strategy. As an action of the agent, a regulator factor is used to coordinate the intuitive approach and the deliberate network. A reward function is designed to balance the exploration and exploitation for large deformation. Successful simulation results verify that the proposed framework can manipulate the soft tissue while avoiding obstacles and adding new position constraints. Compared with the soft actor-critic (SAC) algorithm, the proposed framework can accelerate the training procedure and improve the generalization.

Index Terms—Soft tissue manipulation, grasping point selection, deep reinforcement learning, prior knowledge.

I. INTRODUCTION

Robotic-assisted minimally invasive surgery has promise for improving the flexibility and control accuracy of instruments. Over the past two decades, many surgeons have performed laparoscopic surgery assisted by robotic systems, such as radical laparoscopic prostatectomy assisted by the da Vinci surgical system. However, most surgeons use the teleoperation system to control the instruments. Now roboticists try to increase the levels of autonomy for surgical robots [1], for example, automatic suturing [2], [3] and cutting [4]. One of the key issues of autonomous robotic surgery is automatic soft tissue manipulation, which should often be performed before suturing and cutting.

Many previous studies successfully manipulated the cloth and string-like objects to the desired deformation. Only a few studies were carried out on soft tissue manipulation [5]–[8]. Compared with cloth and string-like deformable objects, the soft tissue is constrained by other connected organs and instruments in the in vivo environment. These connections may be changed because of the operation, such as pulling and cutting. Moreover, surrounding tissues or instruments should be avoided during the soft tissue manipulation period.

Therefore, autonomous soft tissue manipulation with variable constraints is still a challenge.

Preliminary studies explored the dynamics of deformable objects manipulated by instruments. The mass–spring model is often used to simulate the deformable object [9], which is inaccurate for large deformation of soft tissues. The finite-element model is another good approach to simulate soft tissue, but this model is sensitive to the constraints of soft tissue and external disturbances [10]. Few research studies explored the active deformation control when the connection constraints of soft tissue are variable and unknown, which is a common situation in laparoscopic surgery. Moreover, soft tissues have infinite degrees of freedom (DOFs), which brings challenges to estimating their shape and physical parameters in the in vivo environment. Furthermore, the carefully designed controller based on the dynamics may become unstable because of uncertainties and inaccurate estimation parameters. Hence, achieving the performances of deformation control strategies based on the accurate model in actual robotic surgeries is difficult.

By contrast, some researchers appear to investigate model-less approaches for soft tissue manipulation. For example, Navarro-Alarcon et al. [5], [11] tried to estimate the deformation Jacobian matrix of soft tissue in real time and designed an adaptive controller with visual feedback. The deformation Jacobian matrix is a linear approximation of the deformation model in a short time, which works well if the instruments move slowly. Hu et al. [12] proposed approximating the map between the instrument’s movement and the deformation using a deep neural network (DNN). An online learning approach is used to update the neural network. The learned DNN controller may fail because of limited online data when an external force is suddenly applied to the soft tissue.

Recent success in reinforcement learning, such as solving Rubik’s Cube with a robot hand [13], provides promise for soft tissue manipulation. Sahba et al. [14] employed Q learning to manipulate a soft tissue, where the agent has only 25 possible actions. Shin et al. [6] compared the reinforcement learning and imitation learning approaches for soft tissue manipulation. Both approaches can achieve the manipulation task, but imitation learning can reduce the amount of exploration. To accelerate the training procedure, the policy network is initialized through imitation learning in some deep reinforcement learning frameworks [15], [16]. However, demonstrating all of the soft tissue manipulation scenarios is impossible because of the high-dimensional deformation space and variable contact conditions.

This work was supported by the National Key Research and Development Program of China (Grant No. 2021YFC0122602). The authors are with the School of Management, Hefei University of Technology, Hefei, China and the Key Laboratory of Process Optimization and Intelligent Decision-Making (Ministry of Education), Hefei University of Technology, Hefei, China (emails: lxxxxxxian@gmail.com, zshuai_9508@163.com, yangs1@hfut.edu.cn, booyang@hfut.edu.cn).
constraints. The demonstration trajectories may be generated by different experts. The distribution between the demonstrations and test scenarios may be non-identical.

To simplify the scenario, many existing algorithms assume that the manipulation point is appropriately selected before the deformation control and the soft tissue can be manipulated to the target deformation. However, the grasping point should be reselected to avoid over deformation during the training process, which is also a typical case in practical surgery. Some researchers explored the manipulation point adjustment issue in recent year. Sundaresan et al. [17] presented a grasping point selection method by defining a disentangling hierarchy over cable crossings for robotic untangling of cable. Huang et al. [18] proposed an active adjustment algorithm for soft tissue manipulation with non-fixed contact. The contact area can be adjusted by sliding the end effector, but the grasping point is fixed unless opening the grasper. Therefore, grasping point selection for soft tissue manipulation is still an unexplored topic.

We propose a deep reinforcement learning framework with prior knowledge for soft tissue manipulation under unknown constraints. The agent is similar to the brain that has two modes of thinking: the intuitive and the deliberate mode. The intuitive mode is defined by a simple manipulation approach that the agent always pulls the soft tissue toward the target deformation. The soft actor-critic (SAC) algorithm [19], [20] is applied to tackle complex manipulation issues, such as avoiding obstacles. The agent coordinates the two modes by regulating a weight, which is set as action and updated by the manipulation policy based on the last state. The grasping point selection is treated as a contextual bandit problem [21]. The agent learns the grasping point selection policy using deep Q learning [22]. The final state-action value represents the success rate of each grasping point. The agent selects the optimal grasping point based on the success rate, given the desired deformation. We explore three types of deformation tasks in this paper. When the target deformation is described by a curve or a region, the reward is determined by the feature point farthest to the target. To overcome the long horizons, a piece-wise reward function is designed for large deformation tasks. A piece-wise reward function is further presented to guide the exploration and exploitation in large deformation tasks.

The main contributions of this study are summarized as follows:

1) We propose a reinforcement learning framework for deformation control of soft tissue under unknown constraints. Previous studies suppose the constraints of soft tissue are constant and no obstacles. The proposed framework does not initialize the policy with demonstrations but incorporates an intuitive manipulation approach into the reinforcement learning framework. The agent activates the deliberate policy by an action.

2) We present an autonomous grasping point selection algorithm using deep Q learning for soft tissue manipulation.

Existing research assumes an appropriate grasping point has been selected before soft tissue manipulation. The proposed algorithm can determine the optimal grasping point given the target deformation based on the state-action value. This proposed pipeline promises an automatic training process for soft tissue manipulation.

3) We explore three types of deformation control tasks and their reward functions. In [6], [14], they only investigate position-based deformation, and the reward functions are inapplicable to the curve-based and region-based deformation. A piece-wise reward function is further presented to guide the exploration and exploitation in large deformation tasks.

II. OVERVIEW AND PROBLEM STATEMENT

Active soft tissue manipulation are mainly developed for assisting surgeons in this paper. The agent is similar to a physician assistant in robotic surgery. The deformation of soft tissue $X$ is described as the set of feature points $x_i(t)$ on the surface, which provides the possibility to identify constraints. Although Fast Point Feature Histogram (FPFH) [23] can be used to encode the deformation, FPFH is not intuitive for the surgeon. The deformation of soft tissue is subject to fascias and instruments in the in vivo environment. Position constraints are defined as the part of the tissue that cannot move during manipulation, i.e., $x^{c}_{q}(t) = x^{c}_{q}(0)$, where $x^{c}_{q} \in X$, $p = 1, \ldots, P$, and $P$ is the total number of constant position constraints. Two types of unknown constraints of soft tissue are considered [see Figure 1(a)]: new position constraints $x^{n}_{q}(t) = x^{n}_{q}(\tau)$ and unknown force constraints $f_{l}(t)$, where $x^{n}_{q} \in X$, $\tau$ is a piece-wise function with respect to the time $t$, $q = 1, \ldots, Q$, $l = 1, \ldots, L$, and $Q$ and $L$ are the total number of each constraint, respectively. For example, an additional grasping point, the forces applied by a visceral fascia, just name a few.

The deformation control tasks mainly include pulling part of the tissue to the target region or the tip of a needle and
shaping the contour line to the desired curve. Surgeons rarely
give the global deformation of soft tissue in surgery. Hence, we
present three definitions of local target deformations for soft
tissue manipulation with visual feedback [see Figure 1(b)].

1) Position-based deformation: The target deformation is
given by the position $\mathbf{v}^g$ of a feature point $\mathbf{v}^f \in X$.
Position-based deformation control is a basic operation
task in soft tissue manipulation.

2) Curve-based deformation: The target deformation is de-
scribed by a curve. In this paper, the curve is determined
discretely by points $\mathbf{y}_j$.

3) Region-based deformation: A part of the tissue is manip-
ulated to the target region for cutting or exposure tissue. The
region is given by the center $\mathbf{o}_h$ of a circle and its
diameter $d_c$ in this paper.

Most robot systems for laparoscopic surgery only provide
stereo vision, but the surgery can be performed by the surgeon
successfully. It is also difficult to detect the force from the en-
vironment in robotic surgery. Hence, we explore the soft tissue
manipulation to solve the problem because of the unknown constraints and
disturbances from the

We propose a reinforcement learning framework. If the agent cannot well manipulate the
movement of the grasper. Here, we suppose an appropriate
initial grasping point is selected.

Similar to the brain, we designed two modes of thinking
for the agent: the intuitive and the deliberate mode. We
try to find a simple control approach $\pi_{im}(S_t)$ from actual
surgery, for example, pull a feature point toward the target
point in the position-based deformation control task, i.e.,
$\pi_{im}(S_t) = K_p(\mathbf{v}^d - \mathbf{v}^f)$. A model-free fuzzy controller is
another good option. However, the simple control approach


can only achieve a few deformation tasks. The deliberate mode
should be activated at a complex situation. SAC is employed
to train the manipulation policy $\pi_{dm}(S_t)$ in deliberate. One of
the issues is when to activate the deliberate mode, i.e., how to
evaluate the reliability of each model. We set $\alpha(t)$ as an action
of the actor. The output of $\pi_{dm}(S_t)$ includes the movement of
grasper and the complex index. To coordinate the two control
modes, the movement of the grasper is expressed as

$$a_t = \alpha(t) * W_{a} \pi_{dm}(S_t) + (1 - \alpha(t)) * \pi_{im}(S_t)$$

where $W_{a} = [I_3 \ 0]$, and $\alpha(t) \in [0, 1]$. The reliability $\alpha(t)$ is
updated in real-time according to the state. When $\alpha$ is close
to 0, the agent inclines to use $\pi_{im}$. As $\alpha$ is close to 1, the
deliberate mode $\pi_{dm}$. The proposed framework can also be
used to coordinate the surgeon and the machine behavior in
robotic surgery. Training details can be found in Algorithm 1.

### Algorithm 1 Soft Tissue Manipulation with IM_SAC.

Initialize parameters $\theta_1, \theta_2$ and $\varphi$
Initialize replay memory $D$ to capacity $H$
Select initial grasping point $G$

For episode $= 1, ..., M$ do

For $t = 1, ..., N$ do

Input $s_t$ to the SAC actor and output $\alpha(t), \pi_{dm}(s_t)$

$a_t \leftarrow \alpha(t) * W_{a} \pi_{dm}(s_t) + (1 - \alpha(t)) * \pi_{im}(s_t)$

Execute action $a_t$ and observe reward $r_t$, done $d_t$, and next state $s_{t+1}$

Store transition $\{s_t, a_t, r_t, s_{t+1}, d_t, \alpha(t)\}$ in $D$

Sample random minibatch from $D$ to calculate $Q(s, a, \alpha)$ to update $\theta_1, \theta_2$ and $\varphi$

End For

End For

The state $S(t)$ is defined as the set of feedback points $\mathbf{x}_i(t)$, the
target points $\mathbf{y}_j$, the grasping point $\mathbf{v}^g(t)$, obstacles $\mathbf{o}_h$ and the
constant position constraint $\mathbf{x}^p_f$. Inputting these features to the
neural network assists the agent realize the unknown
constraints during manipulation. The action $A_t \in \mathbb{R}^3$ is set as the
movement of the grasper. The state $S(t)$ is close

$$min \mu(\mathbf{x}_1, \ldots, \mathbf{x}_K, \mathbf{y}_1, \ldots, \mathbf{y}_M)$$

s.t.

$$\mathbf{x}^p_f(t) = \mathbf{x}^p_f(0), p = 1, \ldots, P$$

$$\mathbf{x}^g_q(t) = \mathbf{x}^g_q(\tau), q = 1, \ldots, Q$$

$$\mathbf{x}_l(t) = \mathbf{x}_l(t) + \omega(\mathbf{f}_l(t)), l = 1, \ldots, L$$

$$\mathbf{v}^g(t) - \mathbf{o}^b_h \notin B^O_h, h = 1, \ldots, H$$

$$\mathbf{v}^g(t) \in B^s$$

where $\mu(\cdot)$ denotes the measure function of the error between
the current state and the target deformation, $\mathbf{y}_j$ represents
the discrete points for defining the target deformation, $\mathbf{x}^p_f$ is the
position of the $i$th feature point without disturbances, $B^s$ is the
position bound, respectively, $\mathbf{o}_h$ is the center of the $h$th obstacle
$B^O_h$ denotes obstacle space, and $\omega(\mathbf{f}_l(t))$ represents the
placement caused by the $h$th unknown force constraint.
Control and planning algorithms based on models is unreliable to
solve the problem because of the unknown constraints and
disturbances from the in vivo environment. Hence, we explore
model-free reinforcement learning for solving the soft tissue
manipulation problem.

### III. METHODS

#### A. Reinforcement Learning with Manipulation Knowledge

To deploy the reinforcement learning in soft tissue manipulation,
we have to address two questions: what is the optimal
initial grasping point given the target deformation, and how to
manipulate the soft tissue under unknown constraints. The first
question is depend on the second question in the reinforcement
learning framework. If the agent cannot well manipulate the
soft tissue, the evaluation of the initial grasping point is
inaccurate. To tackle this problem, we propose a reinforce-learn.
ning framework with manipulation knowledge for soft
tissue manipulation.

#### B. Reward Design

We explore the reward design problem for the target deform-
ations described by single or multiple points. In a position-
based deformation control task, the agent gets a penalty of
$-\rho \parallel \mathbf{d}(t) \parallel$ at any time, where $\mathbf{d}(t) = \mathbf{v}^g(t) - \mathbf{v}^f$, such that the
agent tries its best to find the optimal trajectory. If the grasper
goes out of the boundary, the agent gets a penalty $R_b$. When
to curve-based deformation, we set the penalty signal \( R \), the target deformation is described by multiple points, such as \( Z \) divide into complex scenario. To overcome the long horizon, we try to intuitive manipulation approach mentioned in previous section the goal. The reply buffer stores many invalid data. The problem because the grasping point cannot be changed during soft tissue manipulation. The grasping point is similar to the \( C \). Grasping Point Selection

the target deformation, the reward is calculated based on the trajectory: 

\[
R_d = 1 - \sum \| d(t) \| / \sum \| d(0) \| \quad (5)
\]

\[
R_g = 1 - \beta_g \left( \sum \| g(t) \| - \sum \| g(0) \| \right) \quad (6)
\]

\[
r_{g0} = \beta_{g0} \| g(0) \| \quad (7)
\]

\[
r_t = 1 - (n - N') / N \quad (8)
\]

where \( g(t) = v^f - v^i \), \( n \) is the total step, \( N \) is the maximum step, \( N' \) is a step threshold, \( n \) is less than \( N' \), and \( \beta_g \) and \( \beta_{g0} \) are positive constant. The index \( r_d \) means that the deformation is expected to be close to the target deformation during the manipulation process. If most deformation errors are larger than the initial error, the quality of the initial grasping point is poor. The index \( r_g \) evaluates the strain between the grasping the point and the feedback points. If the index \( r_g \) is small, the agent may injure the soft tissue although the feedback points reach the target. The index \( r_{g0} \) constrains that the initial grasping point should be not far away from the feedback points. The index \( r_t \) evaluates the manipulation episode length. After finishing an episode, the agent receives a reward signal \( R_{tr} \):

\[
R_{tr} = 1_{E_{\rho tr}} R_{e}^{in} + (1 - 1_{E}) \rho tr R_{e}^{out} \quad (9)
\]

where \( \rho tr = \lambda tr r_{tr} + \lambda tr r_{g} + \lambda tr r_{g0} - \lambda tr r_{g}^{2} ; \lambda tr(1) \in [0,1]. \) If the grasping point is at the edge, \( 1_{E} = 1 \), and the agent get a reward of \( \rho tr R_{e}^{in} \). If the grasping point is out of the edge, the reward is \( \rho tr R_{e}^{out} \). If the agent fail to control the deformation, but the grasping point is at the edge, the reward is set as \( R_{se} \). Otherwise, the reward is \( R_{fe} \). The total reward can be formulated as 

\[
R_{t} = (1 - 1_{D})(1_{E} R_{se} + (1 - 1_{E}) R_{fe}) + 1_{D} R_{tr} \quad (10)
\]

During the training, a security constraint index \( z_s \) is defined to abandon the manipulation task if the soft tissue is over-deformation:

\[
z_s = \begin{cases} 
1, & \text{if } \sum_{i=N}^{i} 1^i_{S'} \geq \delta \\
0, & \text{otherwise.} 
\end{cases} \quad (11)
\]

where \( S' = \{ s_{i'} | \beta_{se} (\| g(t) \| - \| g(0) \|) > 1 \| d_{i-1} \| < \| d(t) \| \} \), and \( \delta \) is a threshold. If the index \( z_s \) is greater than the threshold \( \delta \), the agent will give up the deformation control task. Deep Q learning is used to train the grasping policy. The normalized final state-action value \( Q_{se} \) indicates the success rate of each grasping point. The agent selects the grasping point based the success rate \( \Omega \) given the target deformation. Training details can be found in Algorithm 2.

C. Grasping Point Selection

The initial grasping point selection is a contextual bandit problem because the grasping point cannot be changed during soft tissue manipulation. The grasping point is similar to the slot machine. If the agent can manipulate the soft tissue to the target deformation, the reward is calculated based on the trajectory of the feedback points. On the other side, the agent must determine when to abandon the manipulation task to avoid over-deformation. We define four indexes to evaluate the trajectory:

\[
r_{d} = 1 - \sum \| d(t) \| / \sum \| d(0) \| \quad (5)
\]

\[
r_{g} = 1 - \beta_{g} \left( \sum \| g(t) \| - \sum \| g(0) \| \right) \quad (6)
\]

\[
r_{g0} = \beta_{g0} \| g(0) \| \quad (7)
\]

\[
r_{t} = 1 - (n - N') / N \quad (8)
\]

Algorithm 2 Initial Grasping Point Selection and Evaluation.

| Initialize replay memory \( D \) to capacity \( H \) 
| Initialize action-value function \( Q \) with random weights \( \theta_1 \)
| Initialize evaluation network \( \psi \) with random weights \( \theta_2 \)
| For \( t = 1, ..., T \) do 
| With probability \( \varepsilon \) select a random action \( a_t \)
| otherwise select \( a_t = \arg\max_a Q(s_t, a, \theta_1) \)
| \( s_{\psi}(t) \leftarrow [v^g, v^f, v^d] \)
| Calculate \( \psi(s_{\psi}(t)) \)
| Execute algorithm 1
| If \( z(t) > \delta \) then 
| Set \( d_t = 0 \) and observe \( r_t \)
| Else 
| observe \( r_t \) and \( d_t \)
| End If
| Store transition \( \{ s_t, a_t, r_t, d_t, s_{\psi}(t) \} \) in \( D \)
| Sample random minibatch from \( D \)
| Set \( y_t = r_t, y_{d_t} = d_t \)
| Calculate \( (y_t - Q(s, a, \theta_1))^2 \) to update \( \theta_1 \)
| Calculate \( (y_{d_t} - \psi(v^g, v^f, v^d))^2 \) to update \( \theta_2 \)
| End For
surface. The liver model is fixed by four constant position constraints, which has 135 grasping points on the surface. We define the shape of the obstacle as a cuboid outside the liver, and the target point is behind the obstacle. The sampling time is 0.02s. Our experiments use one Titan RTX GPU.

In the soft tissue manipulation control tasks, we reduce 181 vertices to 30 using Principle Component Analysis. The state of the actor contains 30 feature points \( x_i \), the target points \( y_j \), initial and real-time position of the grasping point \( v^\rho(t) \), the cuboid obstacle \( a_1 \), three constant position constraint \( x_p^g \) and one unknown position constraint. In position-based deformation control tasks, \( y_j = v^d \), \( \rho = 5 \), \( R_a = 100 \), \( R_b = -1000 \). The details of the reward \( R' \) are shown in Table 1. Four target points are used to determine the target deformation in curve-based deformation control task. In region-based deformation control tasks, the region was described by a sphere with diameter of 1. Eleven feedback points should be manipulated to the sphere. The output action contains the movement of the grasper \( \Delta v^\rho \) and the regulatory factor \( \alpha \). To avoid over-deformation, we set safety space \( B^s \) is a cube with the length of 2, and its center is the initial grasping point. The displacement of the grasper \( \Delta v^\rho \) is limited within the range of \([-0.3, 0.3]\). The input of the critic includes the state of the soft tissue \( S_t \), the displacement \( \Delta v^\rho \), and the regular factor \( \alpha \).

We verified the proposed grasping point selection algorithm in the position-based deformation control task. The state is the initial deformation of the liver model. The actions are 135 grasping points on the surface. The reward \( R_{se} \) and \( R_{fe} \) are set as \(-5000\), and \(-5500\), respectively. The reward \( R_{in} \) and \( R_{out} \) are set as 15 and 10, respectively. We set \( \beta_g = 0.5 \), \( \beta_{p0} = 1/3 \), \( N^t = 750 \), \( N = 800 \), \( \lambda_d = 0.2 \), \( \lambda_d = 0.4 \), \( \lambda_g = 0.4 \), \( \lambda_{p0} = 0.3 \) and \( \delta = 150 \). The output of the evaluation policy is the success rate of the grasping point. The grasping point is reselected when the rate \( \Omega \) is lower than 70% during the manipulation period.

The proposed reinforcement learning framework for the
deformation control under unknown constraints is denoted as IM-SAC. All three proposed networks are MLP with 2 hidden layers of 256 units, as shown in Figure 2. We choose the activation function ReLU and optimizer Adam and set the learning rate to $10^{-3}$. We set the replay buffer size to 2e6, the discount factor $\gamma$ to 0.99, and the batch size to 64. Every $10^4$ cumulative operation, 60% of the time used for training, 40% for testing. Save network parameters every $5 \times 10^4$ times.

**B. Deformation Control Results**

We gave the 100 random target deformation and set three levels of acceptable ranges of error: 0.2, 0.4, and 0.6. We define generalization as the success rate of completing the task among 100 random target points. As shown in Figure 3, the proposed reinforcement learning framework can achieve all of the soft tissue manipulation tasks. The trajectories of the feedback points are shown in Figure 4, where the agent was trained with SAC and the proposed IM-SAC, respectively. We can see that both methods can accomplish the tasks; the proposed IM-SAC has better manipulation trajectories. As shown in Table 2, after $5 \times 10^4$ episodes, we find that the agent trained with IM-SAC can achieve the control tasks. The agent learned to rely on the intuitive manipulation approach. However, the success rate of SAC is still after $1.65 \times 10^6$ episodes. The experiment results show that SAC should be deployed for complex tasks. An intuitive manipulation approach is more suitable for simple control tasks.

To verify the deliberate mode, obstacles and external forces were applied to the soft tissue during the manipulation period. We added new position constraint points and pulled part of the liver model to mimic unknown external forces. As shown in Figure 5, the success rate of IM-SAC is higher than that of SAC after $4 \times 10^5$ episodes, when an obstacle is around the tissue. The 66% generalization of IM-SAC in Table 2 is a

![Fig. 4. Trajectories of feedback points.](image1)

![Fig. 5. Deformation error $d(T)$ during the training.](image2)

![Fig. 6. Performance comparison of different reward functions for position-based deformation. $d(T)$ using different reward functions during SAC-based training.](image3)

![Fig. 7. Coordination between the intuitive and deliberate modes. (a) The trajectories of the policy trained with SAC and IM_SAC. (b) The reliability of each mode.](image4)
Fig. 8. A successful example of autonomously generating initial grasp points based on task 1. The first column shows three different scenes of the initial grasping state, (1-a) represents the static state of the liver model; (2-a) adds unknown dynamic interference based on (1-a); (3-a) adds unknown dynamic interference and constraint areas that cannot be grasped. (a)-(c) represent the process of the agent achieving autonomous grasping point selection and control tasks.

Table II: The training speed and generalization (success rate of 100 manipulations) of our method and SAC are compared on task 1.

| Scene       | Method  | Episode | $v^d \pm 0.2$ | $v^d \pm 0.4$ | $v^d \pm 0.6$ |
|-------------|---------|---------|---------------|---------------|---------------|
| No Obstacle | IM-SAC  | $5 \times 10^3$ | 100% | 100% | 100% |
|             | SAC     | $1.65 \times 10^6$ | 29%  | 9%  | 9%  |
| Obstacle    | IM-SAC  | $4 \times 10^3$  | 66%  | 62% | 56% |
|             | SAC     | $9 \times 10^5$  | 18%  | 9%  | 3%  |
| Obstacle    | IM-SAC  | $1.7 \times 10^9$ | 100% | 100% | 100% |
| + Disturb   | SAC     | $3 \times 10^6$  | -    | -   | -   |
| no piece-wise | IM-SAC | $2 \times 10^6$  | 93%  | 90% | 84% |

result of our testing with the model that implemented the task for the first time, and the generalization can reach 100% as the number of training increases. As shown in Figure 7(a), as the external forces are applied to the tissue, the agent trained with SAC cannot learn the manipulation behaviour after three million episodes. The agent trained with IM-SAC can achieve the deformation task after $1.7 \times 10^6$ episodes. The deliberate mode was activated as the agent encountered the obstacles as shown in Figure 7(b). After avoiding the obstacle, the agent inclines to rely on the intuitive mode. Moreover, the success rate will decrease without the proposed piece-wise reward function, as shown in Figure 6 and Table 2. The proposed piecewise reward function can guide the agent to explore and overcome the long horizon.

C. Grasping Point Selection using Deep Q Learning

The success rate of the proposed reinforcement learning framework is high, such that it can be used to evaluate the quality of the initial grasping points. As shown in Figure 8-S1, the agent selected an appropriate grasping point given the target deformation. Moreover, when an external force is applied to tissue, the agent can still select an appropriate grasping point[see Figure 8-S2]. On the other side, we further
defined a region that cannot be the initial grasping point, similar to a cancerous region. As shown in Figure 8-S3, the agent could find an appropriate grasping point out of the forbidden region. Figure 9(a) shows the reward value of all grasping points on the liver model. Figure 9(b) shows the predicted success rate of these grasping points. Figure 10(a) shows some grasping points on the liver, including those that can and cannot achieve the task. Figure 10(b) shows the predicted success rate of these grasping points. The experiment results verify that the agent can evaluate the initial grasping points for the soft tissue manipulation, and select the optimal grasping point given the target deformation.

V. CONCLUSION AND FUTURE WORK

Active deformation control of soft tissue manipulation is fundamental for autonomous robotic surgery. We propose a reinforcement learning framework incorporating intuitive manipulation knowledge to tackle soft tissue manipulation with variable constraints and autonomous grasping point selection before deformation control. The SOFA simulation platform performs three types of soft tissue manipulation tasks. Experiment results show that the agent can actively select the optimal grasping point given the desired deformation and successfully control the soft tissue deformation as appearing obstacles and applying external forces. The intuitive manipulation knowledge and the designed reward function guide the agent to explore the configuration space efficiently. The deliberate manipulation policy is activated in a complex scenario. The proposed pipeline applies for simulation to real deployment, which will be verified in future work.

REFERENCES

[1] Dupont P E, Nelson B J, Goldfarb M, “A decade retrospective of medical robotics research from 2010 to 2020,” Science Robotics, vol. 6, no. 60, pp. eabi8017, 2021.
[2] Shademan A, Decker R S, Opfermann J D, “Supervised autonomous robotic soft tissue surgery,” Science translational medicine, vol. 8, no. 377, pp. e377ra64–e377ra64, 2016.
[3] Saeedi H, Opfermann J D, Kam M, “Autonomous robotic laparoscopic surgery for intestinal anastomosis,” Science Robotics, vol. 7, no. 62, pp. eabj2908, 2022.
[4] Nguyen T, Nguyen N D, Bello F, “A new tensioning method using deep reinforcement learning for surgical pattern cutting,” in IcIT, 2019, pp. 1339-1344.
[5] Navarro-Alarcon D, Liu Y H, Romero J G, “Model-free visually servoed deformation control of elastic objects by robot manipulators,” TRO, vol. 29, no. 6, pp. 1457–1468, 2013.
[6] C. Shin, P. W. Ferguson, S. A. Pedram, “Autonomous Tissue Manipulation via Surgical Robot Using Learning Based Model Predictive Control,” in ICRA, Montreal, QC, Canada, 2019, pp. 3875-3881.
[7] Mo H, Ouyang B, Xing L, “Automated 3-D deformation of a soft object using a continuum robot,” IEEE Transactions on Automation Science and Engineering, vol. 18, no. 4, pp. 2076-2086, 2020.
[8] Ouyang B, Mo H, Chen H, “Robust model-predictive deformation control of a soft object by using a flexible continuum robot,” in IROS, 2018, pp. 613-618.
[9] Essahbi N, Bouzgarrou B C, Gogu G, “Soft material modeling for robotic manipulation,” in Applied Mechanics and Materials, 2012, pp. 184-193.
[10] Kaufmann P, Martin S, Botsch M, “Flexible simulation of deformable models using discontinuous galerkin fem,” Graphical Models, vol. 71, no. 4, pp. 153-167, 2009.
[11] Navarro-Alarcon D, Yip H M, Wang Z, “Automatic 3-d manipulation of soft objects by robotic arms with an adaptive deformation model,” TRO, vol. 32, no. 2, pp. 429–441, 2016.
[12] Hu Z, Han T, Sun P, “3-d deformable object manipulation using deep neural networks,” RAL, 4(4): 4255-4261, 2019.
[13] OpenAI I A, Andrychowicz M, Chociej M, “Solving rubik’s cube with a robot hand,” arXiv preprint arXiv:1910.07713, 2019.
[14] Pedram S A, Ferguson P W, Shin C, “Toward synergic learning for autonomous manipulation of deformable tissues via surgical robots: An approximate q-learning approach,” in BioRob, 2020, pp. 878-884.
[15] Fujimoto S, Meger D, Precup D, “Off-policy deep reinforcement learning without exploration,” in ICML, 2019, pp. 2052-2062.
[16] Gao Y, Xu H, Lin J, “Reinforcement learning from imperfect demonstrations,” arXiv preprint arXiv:1802.05313, 2018.
[17] Viswanath V, Grannen J, Sundaresan P, “Disentangling Dense Multi-Cable Knots,” in IROS, 2021, pp. 3731-3738.
[18] J. Huang, Y. Cai, X. Chu, R. H. Taylor and K. W. S. Au, “Non-Fixed Contact Manipulation Control Framework for Deformable Objects With Active Contact Adjustment,” RAL, vol. 6, no. 2, pp. 2878-2885, 2021.
[19] Haarnoja T, Zhou A, Abbeel P, “Soft actor-critic: Off-policy maximum entropy deep reinforcement learning with a stochastic actor,” in ICML, 2018, pp. 1861-1870.
[20] Haarnoja T, Zhou A, Hartikainen K, “Soft actor-critic algorithms and applications,” arXiv preprint arXiv:1812.05905, 2018.
[21] Sutton R S, Barto A G, Reinforcement learning: An introduction. MIT Press, 2018.
[22] Mnih V, Kavukcuoglu K, Silver D, “Human-level control through deep reinforcement learning,” nature, vol. 518, no. 7540, pp. 529-533, 2015.
[23] R. B. Rusu, N. Blidow, and M. Beetz, “Fast point feature histograms (FPFH) for 3d registration,” in ICRA, 2009, pp. 1848–1853.
[24] F. Faure, C. Duriez, H. Delingette, J. Allard, B. Gilles, S. Marchesseau, H. Talbot, H. Courtecuisse, G. Bousquet, I. Peterlik, et al., “SOFA: A Multi-Model Framework for Interactive Physical Simulation,” in Soft Tissue Biomechanical Modeling for Computer Assisted Surgery, Springer, 2012, pp. 283–321.