Robotic Assisted Puncture Intervention with Respiratory Status Monitoring

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***Abstract*— We propose a robotic-assisted abdominal puncture intervention with respiratory status monitoring in this paper. We constructed the collected respiratory data as point cloud data and established a respiratory state monitoring model using the Pointnet++ point cloud classification network. During normal respiration, We divided the respiratory signal into four phases: inspiration, peak inspiration, expiration, and the valley of expiration, and used the peak respiratory phase as the robot's needle Intervention moment. Experiments with simulated robot-assisted puncture interventions show the proposed scheme is feasible in a robot-assisted puncture intervention system.**

I. INTRODUCTION

The respiratory motion of the human body cause irregular displacement of abdominal organs and tumours. Therefore, robotic-assisted abdominal puncture interventions must have a solution to the respiratory problem.

Real-time tracking of the tumour is one of the best solutions to the respiratory problem. It can achieve by establishing a correlation model between the monitored external signal and the internal tumour motion trajectory. To track the tumour in real-time, a puncture fiducial needle can be implanted near the tumour to establish a real-time deformation model of the internal fiducial marker and the tumour[1]. A respiratory motion model also can be found from the surface fiducial marker[2]. An artificial neural network model can also predict the tumor position under respiratory motion in real-time[3]. These methods are all based on the assumption that external signals strongly correlate with internal tumour motion. However, this assumption does not necessarily hold from a physiological perspective [4].

Respiratory gating is the simplest and most effective solution to the problem of respiratory during robot-assisted abdominal puncture interventions. Varian USA manufactures the True Beam system [5], which is the world's most advanced respiratory gating device and has been widely used in oncology radiology. In addition, it is possible to apply respiratory gating to abdominal puncture. It is achieved by quantifying registration errors in real-time to compensate for robot motion in surgical navigation [6].

This paper aims to construct a solution to the problem of respiratory during robot-assisted abdominal puncture interventions, using respiratory status monitoring and respiratory gating techniques.

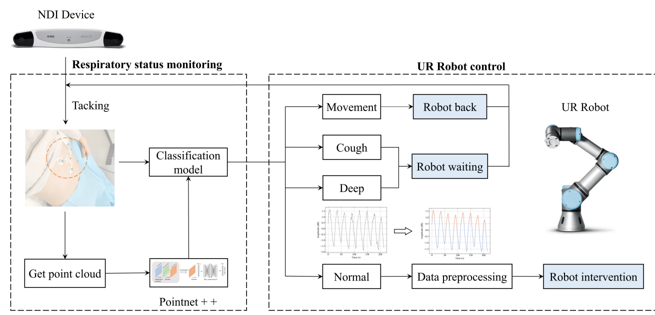

Fig. 1. Robotic Assisted puncture intervention scheme

II. METHODOLOGY

The robotic abdominal puncture intervention we constructed consists of respiratory status monitoring and the robot control module, as shown in Figure 1. The respiratory status monitoring module uses the monitored respiratory status as a command to guide the robot's movement in real-time. When an abnormal respiratory state is detected, the robot hovers or returns to its initial posture and waits. When a normal state is detected, the peak inspiratory moment is determined as the moment of needle insertion by analyzing and processing the average respiratory signal.

To achieve real-time respiratory status monitoring, respiratory data were collected for normal respiratory, deep respiratory, cough, and other abnormal movement conditions. The data was collected with the subject lying still on the acquisition platform, and five NIR reflective spheres were attached to the right rib cage of the issue in a set distribution as a fiducial mark, as shown in Figure 2. Respiratory data were collected from 19 healthy adult males for 3 hours using the NDI Polaris Vega ST.

The point cloud data is constructed from the continuously transformed coordinate values of the five fiducial markers over one second. The point cloud classification network model Pointnet++ [7] changes the respiratory state classification into a point cloud classification question. Since the point cloud data of respiration contains fewer points

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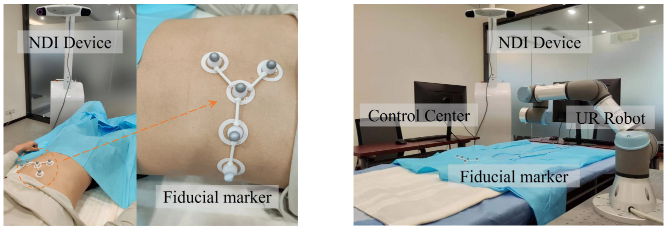


(a) Respiratory data collection (b) Experimental platform

Fig. 2. (a) shows how respiratory data is collected and where the fiducial marker is attached. (b) Shows an experimental platform for simulating abdominal puncture interventions

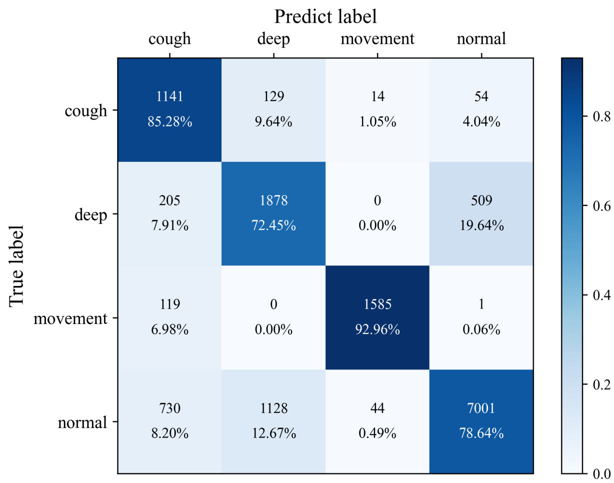


Fig. 3. Accuracy of classification for each respiratory state

and less information, the original feature extraction layer of Pointnet++ is reduced by half. The absoulte accuracy of the respiratory state classification model is 81%, where the accuracy of the individual respiratory states is shown in Figure 3.

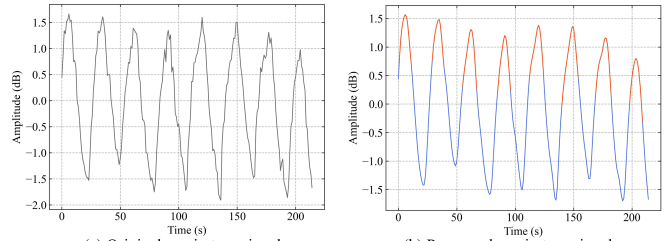
When the respiratory state monitoring model monitors the normal respiratory state, a respiratory curve is inscribed using the amplitude of motion of the fiducial marker center of mass. It is filtered into a stable sinusoidal-like turn using an averaging smoothing method by eq(1).

$$x_i^{'} = \frac{(x_{i-1} + x_{i+1})/2 + x_i}{2} \tag{1}$$

where $i = (2, 3, \ldots n-1)$, and $x \in X = \{x_1, x_2, \ldots x_n\}$ is the amplitude of motion of the fiducial marker center of mass after standardization.

The normal respiratory signal was divided into four respiratory phases based on the monotonicity of the curve: inspiration, expiration, peaks, and valleys. We have observed that the increasing curve corresponds to the inspiratory phase and the exhalation to the decreasing curve. We have observed that the increasing curve corresponds to the inspiratory phase and the exhalation to the decreasing curve. The peak respiratory phase is shown in Figure 4.

The optimum puncture time for the robot is determined from the preoperative CT recording of the respiratory phase.



(a) Original respiratory signal (b) Processed respiratory signals

Fig. 4. (a) is the original normal respiratory signal collected. (b) shows the phase of the respiratory peak captured after smoothing.

During abdominal puncture interventions, if a respiratory phase can be traced intraoperatively to be similar to the preoperative CT, the tumor's location in the target area is identical a the preoperative CT. In the clinic, the respiratory phase recorded on the preoperative CT is often the peak respiratory.

III. Results

By collecting respiratory data from different respiratory states and constructing them as point clouds, we achieved real-time monitoring of the intraoperative patient's respiratory state based on a point cloud classification model. In the normal respiratory state, we divide the respiratory signal into four phases and use the peak respiratory phase as the moment of puncture intervention for the surgical robot.

IV. Conclusions and Discussion

The respiratory status monitoring model with robot control establishes a safety warning mechanism for the abdominal puncture intervention robot, reducing the risk of surgery due to abnormal respiratory status. Finally, we expect to be able to implement the respiratory gating technique with the patient in a free-respiratory state. This will avoid preoperative respiratory exercises and reduce intraoperative patient discomfort.

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