Breathing Motion Compensation Based on Long Short-Term Memory Network for Minimally Invasive Pedicle Screw Placement

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INTRODUCTION

Spinal diseases such as spinal degeneration and scoliosis might require pedicle screw placement (PSP) as a crucial step during surgical interventions, depending on the severity. This procedure requires the drilling of a hole for placing the screw. Thanks to imaging modalities such as computed tomography and intraoperative fluoroscopy, moving from an open approach to minimally invasive surgery (MIS) has been possible and has reduced patient complications after surgery. Still, it suffers from a lack of visual feedback for the surgeon, whereas robotic-assisted spine surgery combined with such imaging modalities can improve surgical outcomes for PSP. Yet, in such MIS procedures, physical motion, such as breathing motion, can induce shifts and deformations in the spine, leading to operation errors of approximately 2-3 mm [1]. In order to correctly identify the entry point, breathing motion needs to be compensated for. External sensors, such as an optical tracking system or range imaging, can be used to measure the motion of the skin or neighboring vertebrae, close to the entry point [2], [3]. However, Saghbiny et al. showed that the amplitude of breathing motion changes over vertebrae and has a variation of 68% from the lumbar to thoracic vertebrae [4]. Therefore, this work develops an approach for estimating the motion of each entry point, enhancing the accuracy. The proposed method uses a long short-term memory network (LSTM) on top of the inner control loop to estimate breathing motion parameters for each pedicle drilling individually, and its output is utilized to update the motion model for motion compensation during robot-assisted drilling for MIS-PSP.

MATERIALS AND METHODS

The experimental setup consists of a robotic drill system with a robot arm (KUKA Robot Med7, Augsburg, Germany) and a custom-designed drilling system with a force/torque sensor (Nano25, ATI). An optical tracking system (FusionTrack 500, Atracsys, Switzerland) is used to track poses. An ex vivo pig spine is placed on a breathing platform, shown in Fig. 1 (a), which generates a one-degree-of-freedom breathing motion. During MIS-PSP, an optical marker is pinned to the spinous process of a vertebra, which is close to the interested drilling

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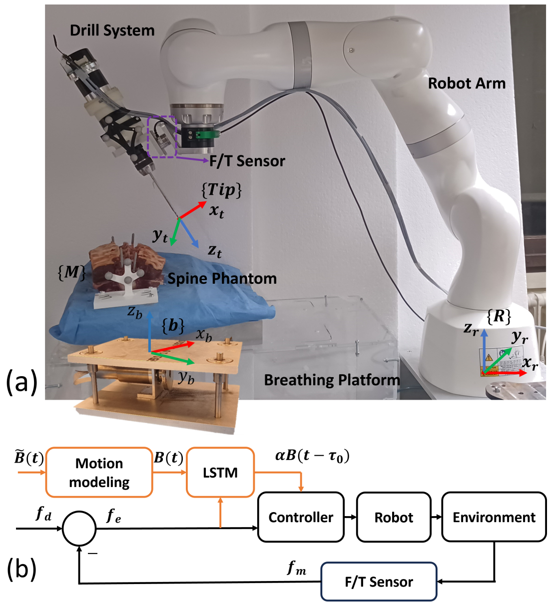

Fig. 1: (a) Illustration of the robotic drilling system for MIS-PSP. (b) Control block diagram of the proposed LSTM-based breathing motion compensation.

vertebrae. Two challenges are identified. First, in an in vivo procedure, moving from vertebrae L5 to L1, the breathing amplitude changes from 2.2 mm to 3.7 mm, corresponding to a rise of 68% in amplitude [4]. Thus, the optical marker can not measure the local information for each vertebra correctly. Second, since the vertebrae levels change during drilling and the soft/hard tissues have an unknown stiffness, the robotic response time delay also changes for each pedicle drilling. These two challenges are addressed in this study: identifying the variable breathing amplitude through a scaling variable α and the variable time delay τ_0 for each pedicle drilling. Because of the complex environment, a data-driven approach, such as LSTM, helps tackle this complicated problem. The LSTM ability to learn historical information and use prior knowledge to predict system behavior at future times has formed a key motivation for using this network for this application. The control block diagram of the proposed system is illustrated in Fig. 1 (b). An inner control loop is used to maintain the constant desired force f_d during the pedicle drilling; on top of it, an LSTM-based motion compensation generates the corresponding motion profile for the controller. Each vertebrae motion $\hat{B}(t)$ can be modeled as $\hat{B}(t) = \alpha B(t - \tau_0)$. $B(t)$ is the periodic

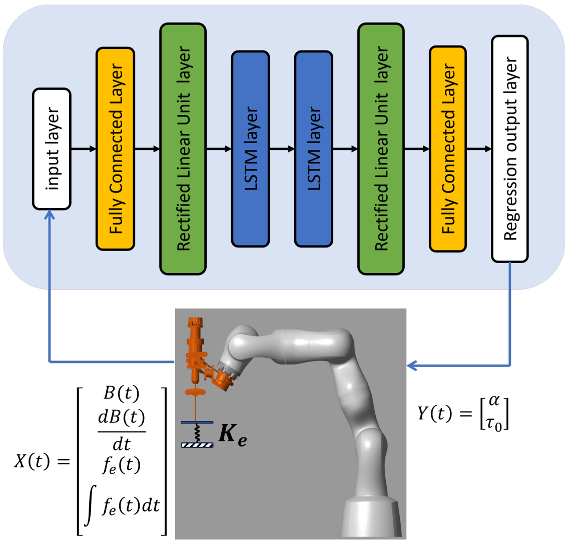

Fig. 2: The LSTM-based deep learning network and the simulation environment.

breathing motion that is estimated with

$$B(t) = a_0 + \sum_{n=1}^{3} a_n \cos(n\omega_0 t) + b_n \sin(n\omega_0 t)\,, \quad (1)$$

where a_0, a_n, and b_n are the estimated coefficients, ω_0 is breathing frequency, and t is time. To estimate the coefficients from the measured breathing motion $\tilde{B}(t)$, the following cost function is optimized:

$$J = \int_{t-T_0}^{t} \left(\tilde{B}(t) - B(t)\right)^2 \, dt\,, \quad (2)$$

where T_0 is the optimization horizon. Within this work, a 2-layer stacked LSTM with 50 neurons was used Fig. 2. Two fully connected layers, input and output of dimension 50, were added before and after the LSTM. The LSTM is trained with the following input and output vectors:

$$X(t) = [B(t), \frac{dB(t)}{dt}, f_e(t), \int f_e(t)dt]^T, Y(t) = [\alpha, \tau_0]^T\,, \quad (3)$$

where $\frac{dB(t)}{dt}$ and $f_e(t)$ are the derivative of modeled breathing motion and drill tip force error. To train the deep learning network, a simulation-based dataset is generated, the robotic drilling system is modeled within Matlab Simscape Multibody, where the environment is modeled with constant stiffness $K_e \in [2, 3.5]$ N/mm for one simulation, and a pig breathing profile is utilized to simulate breathing motion [4]. 600 combinations of $\alpha \in [0.3, 1.7]$, $\tau_0 \in [-1.5, 1.5]$ s and K_e are generated with uniform distribution. For each combination, the corresponding breathing motion $\hat{B}(t) = \alpha B(t - \tau_0)$ is simulated to generate the input $X(t)$ and output $Y(t)$ vectors of the LSTM. 70% of this matched info is used to train the network, and the remaining 30% are considered ground truth test data to infer the original α and τ_0 that were used to simulate the system.

RESULTS

The performance of the trained network is evaluated on 180 configurations of ground truth test data; an example is depicted in Fig. 3. The error between ground truth and estimated values from LSTM $\alpha_{LSTM}, \tau_{LSTM}$ is used for evaluation; the mean error, standard deviation, maximum absolute error, and mean absolute error, are summarized in table I, The value below for each criterion shows the improvement percentage. The proposed system demonstrates a 35.7 ms time delay error and reduces the amplitude scale error to 0.0732.

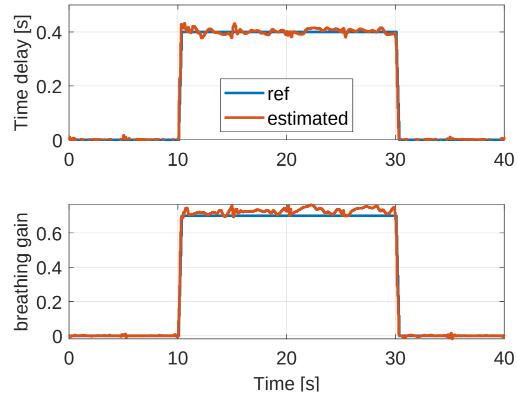

Fig. 3: An example of the time delay τ_0 and breathing amplitude scale α estimation overtime.

TABLE I: Deep learning-based estimation error

	Mean	Std	Max-abs	Mean-abs
Amplitude scale $\alpha - \alpha_{LSTM}$	-0.0140 (99.0%)	0.0382 (2.72%)	0.149 (89.3 %)	0.0732 (94.8 %)
Time delay $[ms]$ $\tau_0 - \tau_{LSTM}$	6.20 (99.6 %)	25.6 (0.850%)	75.8 (97.5%)	35.7 (98.8%)

CONCLUSIONS AND DISCUSSION

This study presents a deep learning-based method for mitigating environmental and system uncertainty during breathing motion compensation for MIS-PSP. The proposed framework uses an LSTM-based method to individually identify the amplitude scale and time delay error for each pedicle drilling. Validation of the proposed system in simulation shows that it can reduce the error in time shift to 35.7 ms, and the amplitude scale error can be compensated 94.8%. This approach embeds intelligence in the robotic PSP system, making it robust to environmental changes. However, further validation through ex vivo or in vivo trials is essential to assess the performance of the method.

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