Human Expert Skill Transferring and Imitation for Teleoperated Dual-Arm Manipulation

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***Abstract*—Humanoid robots used for medical care, household, logistics are deployed more widely in a complex working context, and a great deal of current robot research focuses on teleoperated high degree-of-freedom control for delicate human skill transferring. However, severe vibration phenomenon caused by unwanted noise usually leads to non-smooth robot trajectory. Although advanced robot arms have been equipped with torque sensors to perform torque control, it is not feasible to deploy widely in different workspaces due to its cost. The work reported a model-free approach as an easy-realized and inexpensive method. First, noise elimination was realized by empirical mode decomposition and Savitzky-Golay filter. Second, regenerating motor controllable trajectory was done by downsampling and quadratic interpolation to re-construct a simpler, accurate trajectory with piecewise constant acceleration. After attenuating unwanted vibration noise and interpolating proper sample points, it was shown that the accuracy was improved by 60% with the proposed approach. The result also demonstrates remote human skill transferring, which matches teleoperated target signals for the human motion to robotic arm kinematic motion.**

***Index Terms*—Humanoid robots, Interpolation, Motion control, Path planning**

I. Introduction

HUMANOID robots have been introduced in the past 20 years [1-6] to extend the human presence into complex workspaces, such as space exploration [7], underwater investigations [8], remote medical care [9], and companion [10]. Based on rapid improvement in robot perception and actuation, humanoid robots are primarily combined with teleoperation systems to transfer human expert skills. For space exploration, a control method of the model-based teleoperation system [11] demonstrated the improvement in robustness against modeling error from the remote site. In this context, time and expertise in robotics are required to construct a model representation, making it infeasible for fast application deployment. Nevertheless, the presence of external noise and undeclared disturbance lead to noisy trajectory and severe vibration, hampering robotic arms to perform sophisticated, human-like manipulation in complex environments.

In order to reduce labor costs and improve operation efficiency, learning from demonstration (LfD) [12, 13] for robot motion control is becoming more prevalent these years. Indeed, in any teleoperation system, precise trajectory planning is of crucial importance in imitating human motion. However, it is not easy to transfer an expert's skill and imitate human motion owing to the difference between human arm movement and robot arms kinematic motion.

Prior LfD research has seen to address two issues in imitating and learning human motion: (1) extracting primitive motion and matching demonstration data to enable a robot to reproduce the motion captured from humans and (2) enhancing the learned control policy to adaptation and generalization beyond just cloning trajectories and actions. This research focused on extracting necessary motion and preparing data for virtual training environments to enable a dual-arm manipulator system in imitating human motion. There are three approaches to capture human demonstration data. First, demonstration data was captured from robots, with a camera mounted on a robot and a human operator wearing a virtual reality (VR) headset that displayed the robot's view [14]. For example, an RGB-D camera combined with a VR headset was used in the Softbank Pepper robot to imitate the user's upper limb pose [15]. Although the research introduced intuitive VR-based teleoperation for the humanoid system, manipulation error could occur when mapping human seven joints motion to Pepper's five joints arm motion. Second, demonstration data could be recorded under human guidance by sensors, such as torque sensors, force sensors, and motion sensors in the exoskeleton for rehabilitation [16] and complex manipulation tasks [17]. Usually, human operators wear motion capture sensors for delicate human motion capturing, such as Leap Motion, Manus SteamVR Tracker, etc.

For the motion planning of upper-limb robot arms, the most prevalent methods are analytic expressions (Fourier transform, polynomial functions) and optimization-based approaches [18]. In order to attenuate noise from target signals and prevent manipulators structure from wearing, prior investigations had introduced multiple approaches to trajectory smoothing. In 2010, a shortcutting heuristic approach [19] was proposed to repeatedly replace the intermediate trajectory with a collision-free segment for many- degrees of freedom (DOF) robot manipulators. However, the time-optimal curves could reduce the resemblance between the original and final trajectory. One study selected minimum jerk and fixed time-optimal trajectories for machine axes [20]. Still, other trajectory smoothing research leveraged filters and neural network-based models to realize smooth and accurate motion in a teleoperated robot head system [21]. These results served as efficient approaches for the low DOF and known kinematic motion, such as autonomous driving cars and unmanned ground vehicles. However, human experts usually perform dexterous movements based on previous experience and instant decisions, which makes simplifying trajectories an improper method.

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In this paper, a new approach was introduced to attenuate noise and regenerate robot trajectory in transferring human expert skills to robotic arm kinematic motion. In the proposed method, robot arms could imitate human motion accurately via noise elimination and quadratic interpolation along target signals. First, undeclared noise was attenuated from captured trajectories via decomposing signals and smoothing out low-magnitude, high-frequency components. Then, a few properly located sample points were selected to regenerate motor-controllable trajectory by second-order polynomial interpolation.

II. Materials and Methods

The experimental setup schemed to build a proficiency-based robot training platform, as shown in Fig. (a), so that human movement was transferred to robotic arm kinematic motion. The human expert's delicate arm motion was captured, followed by attenuating unwanted noise, regenerating motor controllable trajectories, and transferring signals to a virtual training environment.

A. Experimental Setup

Robotic manipulator motor: In dual-arm manipulation, a brushless direct current motor (H54-100-S500-R, ROBOTIS, USA) was used in each robot arm joint to imitate and transfer human expert skill delicately. In Table I, the motor has continuous torque 25.3 N/m, resolution 501,923 pulse/rev, continuous speed 29.2 rev/min, and four operating control modes. In this study, in order to develop an approach for motor without torque control to imitate human arm motion, each motor was set to perform in the velocity control mode.

TABLE I
Hardware Specifications of Brushless DC Motor used for the Dual-Arm Manipulator System

Item	Specifications
Resolution	501,923 pulse/rev
Continuous Speed	29.2 rev/min
Continuous torque	25.3 N/m
Operating modes	Torque control mode Velocity control mode Position control mode Extended position control mode

Motion capture devices: Human arm motion was obtained in the form of several separated angle signals by motion tracking devices in the real world. The devices were mounted on a human operator's arm to capture each movement of seven joints, including 3-DOF in the shoulder, 1-DOF in the elbow, and 3-DOF in the wrist. In this study, motion tracking devices captured human arm movement under 100 Hz.

B. Proposed Method

With 7-DOF human arm movement captured as seven separate trajectories, joint 1 to joint 7 human demonstration data was obtained. Briefly, the goal was to generate motor controllable signals that resembled the actual human arm motion. Among current teleoperated robot systems research, velocity control was often utilized in virtual reality (VR) based framework [22]. However, one-to-one expert skill transferring could not be realized precisely due to the lack of validation procedure in mitigating the kinematic mismatching between humans and robot arms. Hence, the novelty of the proposed work lies in preparing motor controllable signals for a virtual training environment as shown in Fig. 1 (a). Therefore, with the presence of inherent physical tremors and teleoperation sensor noise, attenuating the noise before regenerating motor controllable trajectories is important. As shown in Fig. 1 (b), noise elimination and regenerating motor controllable trajectory were used to transfer the human operator's demonstration signals to the virtual training environment.

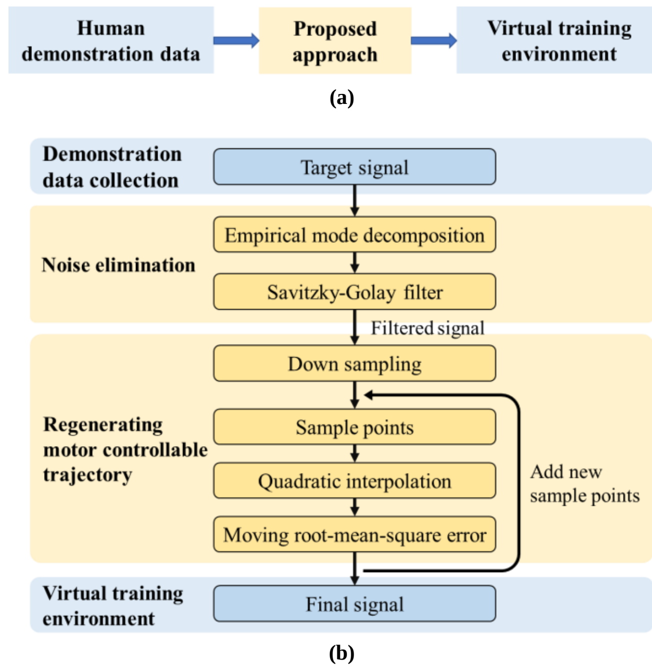


Fig. 1. The proficiency-based robot training platform proposed in this work matched human expert demonstration data to the virtual training environment. (a) a systematic view of the proposed approach (b) a detailed explanation of the proposed method.

For the target signals, preventing unwanted vibration and attenuating noise were preferred. By decomposing a target signal via empirical mode decomposition (EMD), several intrinsic mode functions (IMFs) could be obtained. After the Savitzky-Golay filter (SG filter) smoothing adjacent data on some of the IMFs, quadratic interpolation was used to generate simpler polynomial functions. Few sample points were chosen for the first interpolation, but new sample points were added if the moving root-mean-square error (MRMSE) was too large. By adding more sample points at proper locations, it was ensured that the filtered signal resembled the original one.

C. Noise Attenuation

For motor without torque control, robotic manipulator in velocity control is easier to be achieved by following simpler trajectories. However, the presence of noise hurts robotic arms manipulation, which requires noise to be attenuated before simplifying target signals.

The EMD method introduced by Huang et al. [23] was used in this study to decompose human movement target signals. Since a human operator usually demonstrates delicate manipulation based on previous experience and instant environment dynamics, target signals have a non-stationary and nonlinear frequency in time series. EMD connected local extremes along the signals using cubic splines as envelopes, subtracted the average signal of upper and lower envelopes from the original signal, and retained only some of the components that satisfy the relative sifting tolerance criterion. Then, a sifting process was conducted subsequently to obtain a small number of IMFs that could represent original signals.

Through this approach, non-linear target signals were decomposed into several IMFs, including high- and low-frequency components. It was found that the fast-changing but low magnitude IMF composed of up to 50% of the unintentionally jittered signal. To preserve human motion features and attenuate noise, the SG filter served as a sliding window filter to smooth out some of the high-frequency components and keep others the same. Then, a denoised signal was obtained by synthesizing several IMF components.

D. Regenerating Motor Controllable Trajectory

After the noise elimination process, motor controllable trajectories were generated without severe vibration for velocity control mode. Quadratic interpolation was used to ensure the signal’s second derivative remain constant. Initially, fewer sample points were picked via a higher downsampling operation to avoid the acceleration changing too rapidly. However, a small number of sample points reduced the similarity between the original and the final signal. In order to avoid the acceleration changing frequently, new sample points were added at the proper location each time when the difference was too large.

MRMSE used in this work evaluated the difference between the original signal and the semi-final signal. Apart from a single root-mean-square error (RMSE), MRMSE investigated the difference at each time by a sliding window, making it suitable to serve as an indicator to add new sample points. As a sample point adding indicator, the peak height of MRMSE was used to find the time instant where the error amplitude was larger than a certain value. After the downsampling operation, the MRMSE of the trajectory signal was available. New sample points were added at the locations that the semi-final signal was too different from the original target one i.e., MRMSE peaks. More sample points were added until the final signal resembled the original one. With the proposed approach mentioned above, a simpler polynomial signal that preserved human delicate arm movement features and performed by motors in the velocity control mode was created.

III. RESULTS

As shown in Fig. 2, the joint 7 human demonstration data with severe vibration was motor uncontrollable. In order to generate motor controllable trajectories, EMD was used to decompose human motion signal into several IMFs, as plotted in Fig. 3 (a). It was found that over 50% of the jittered vibration came from high frequency but low magnitude IMF components. Therefore, the SG filter with different sliding window length was used to smooth out each component as plotted in Fig. 3 (b), where noisy IMFs were filtered by longer sliding window length and IMFs with slight change were filtered by shorter window length.

After attenuating noise from non-specific frequency components, a filtered signal was obtained by synthesizing all of the IMFs. However, the number of the sample points in original and filtered signals was 1370, making the fast-changing acceleration signal motor uncontrollable. Therefore, the downsampling parameter was chosen to be 80 to connect fewer sample points at this step.

Second-order interpolation could generate a piecewise constant acceleration path for motors without torque control, and MRMSE was used to improve the resemblance between original and interpolated signals. As shown in Fig. 4, new sample points were added at peaks where MRMSE was too large. After a series of iteration processes to add new sample points, the similarity between original and final signals has been improved. An accurate final signal was plotted in Fig. 5, where unwanted vibration has been attenuated. Compare the original signal with the final signal, the range of acceleration was reduced from 20,000 degrees/s^2 to 300 degrees/s^2 as shown in Fig. 6.

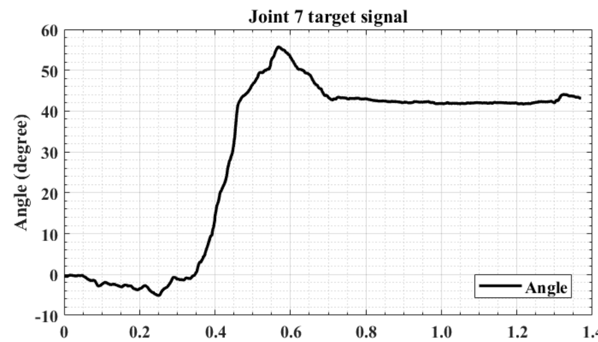
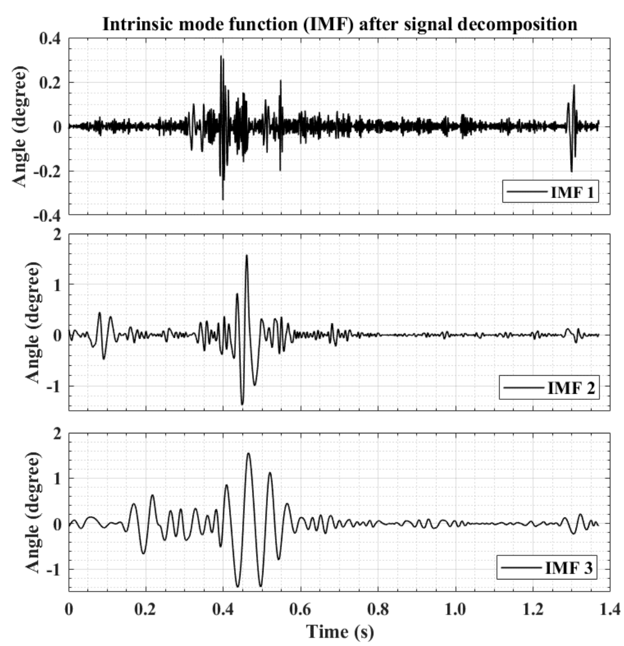
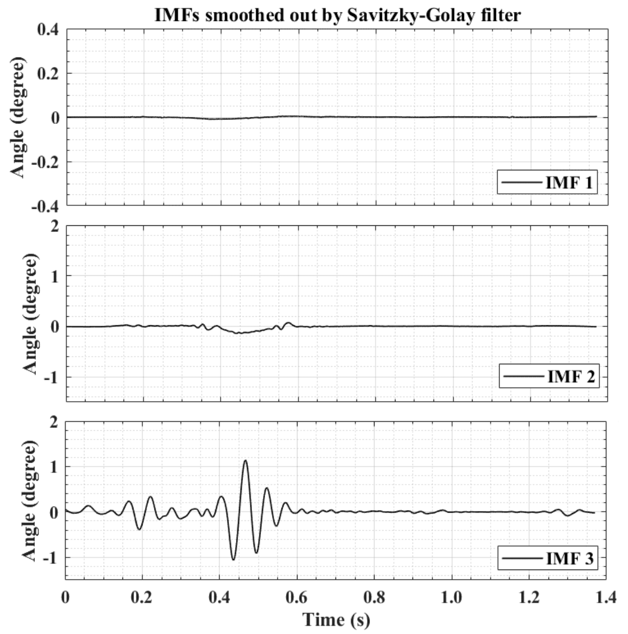


Fig. 2. Joint 7 target signal recorded from human demonstration. Owing to the presence of noise, severe vibration hampered the robot arm to imitate delicate human motion.



(a)



(b)

Fig. 3. Several IMFs decomposed from the target signal were sent to the SG filter and the first three IMFs that contributed unwanted vibration the most were depicted. IMF 1 had a smaller magnitude and higher frequency than IMF 2 and IMF 3, and IMF 3 preserved human movement features the most. (b) data showed that some noisy components were smoothed out by the SG filter from (a).

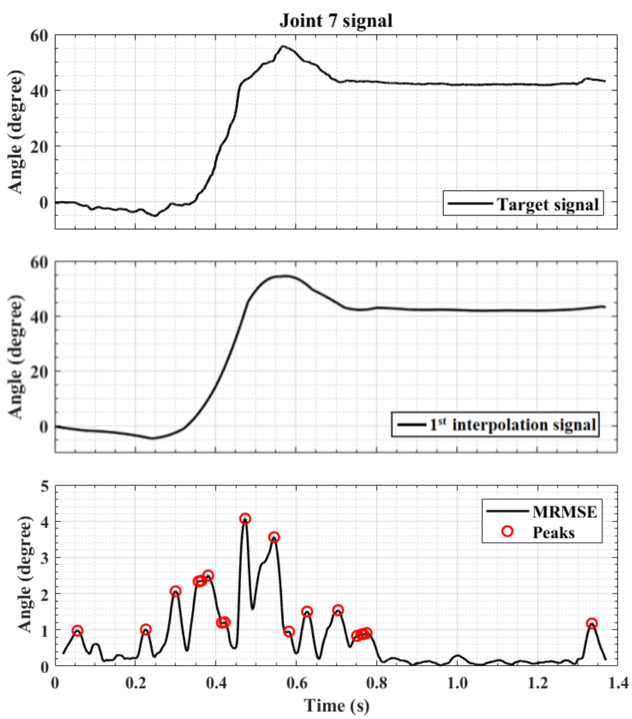


Fig. 4. By subtracting the 1st interpolation signal from the original signal, MRMSE could be obtained. To improve the resemblance, new sample points would be added at peaks as indicated in red hollow circles after several iteration processes.

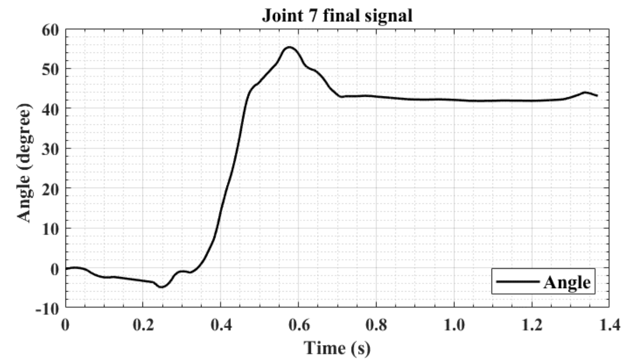


Fig. 5. The figure demonstrated the final angle signal of the joint 7 human arm motion.

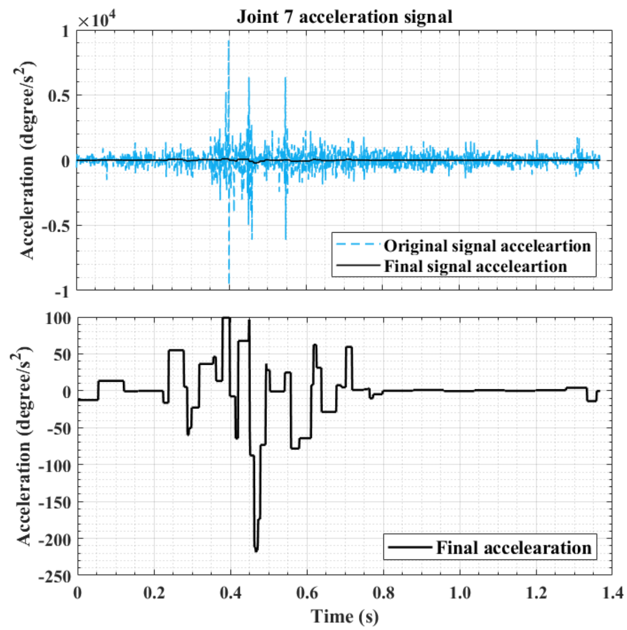


Fig. 6. The figures showed the joint 7 acceleration signal before and after using the proposed approach. (a) comparison of original and final acceleration signal was plotted and (b) demonstrated the piecewise constant path for robotic arms to imitate human motion.

TABLE II
COMPARISON OF SAMPLE POINTS AND RMSE BEFORE AND AFTER A SERIES OF ITERATION BETWEEN JOINT 1 TO JOINT 7 SIGNALS

Joint	Before interpolation		After interpolation	
	Sample points	RMSE (degree)	Sample points	RMSE (degree)
1	19	0.448	26	0.285
2	19	0.480	28	0.254
3	19	0.967	40	0.289
4	19	0.592	28	0.213
5	19	0.742	44	0.304
6	19	0.670	34	0.317
7	19	1.127	59	0.345
Average	19	0.718	37	0.286

Table II demonstrated the improvement of adding new sample points along seven trajectories. When picking fewer sample points after downsampling operation, 19 points were chosen and the RMSE was 0.718 degrees on average. The resemblance was enhanced by adding new sample points at proper locations, and the work improved RMSE by 60% while only 20 to 40 sample points were added. Unlike most computational methods, this study prepared motor controllable trajectories for a virtual training environment. Therefore, transferring human expert skills to teleoperated dual-arm manipulation could be enhanced.

IV. Discussion

The proposed approach provided a novel solution to match human motion to robotic arms kinematic motion, which was a model-free method that could transfer human expert skill fast and wide. Via trajectory signals captured from human arm motion in the form of 7 joints, target signals were used to verify the proposed method.

A. Sliding window length

The sliding window length is an important parameter to ensure the filtered signal be as similar as the original signal recorded from human motion. It was utilized in the SG filter and the MRMSE. Initially, target signals captured from human arm movement remotely came with severe vibration phenomenon, including non-stationary human physiological tremor and teleoperated communication noise. Instead of using the Fourier Transform to filter noise with a specific frequency, the EMD method successfully eliminated the non-stationary frequency noise with only a few sifting operations.

Compared with human physiological finger tremor [24] that has 8~12 Hz postural and kinematic frequency, jittered noise was eliminated over 5 Hz to preserve features for human arm motion in this study. In order to attenuate noise, the sliding window length was chosen based on the shortest distance of local extremes along velocity signals, where the acceleration changed the most. Therefore, the length of 20 sample points was preferred.

B. Downsampling and adding new sample points

To prevent robotic arms from severe vibration, only a few sample points should be selected while regenerating motor controllable trajectories. That meant a bigger downsampling rate and peak height values were preferred. Therefore, the number of sample points was reduced from 1470 to 19 via downsampling operation, leaving only 18 segments along the trajectory. Then, new sample points were added at proper locations that were pointed out by the MRMSE to improve the resemblance.

C. Quadratic interpolation

In the experimental setup section, the BLDC motors in the dual-arm system were used in the velocity control mode. Velocity control motors have a trapezoidal control profile with certain acceleration and de-acceleration values, so the second-order polynomial functions could generate robot controllable trajectories. Most research utilizes high-end torque control robotic arms to perform the human-like motion, but it is expensive and infeasible for wide deployment. A velocity control motor used in this work was an easy-realized method for fast deployment of robot applications. It could prepare noise attenuated, motor controllable trajectories for training models, with a 60% accuracy improvement for the desired teleoperated two-handed manipulation system.

The proposed model-free approach successfully augmented the dexterity of the teleoperated dual-arm robot system in an easy-realized manner, which digitized human expert skills from real-world demonstration and transferred them to a two-handed robot system in the virtual training environment. Beyond the scope of human motion imitation, the perception of the dual-arm robot system could be advanced by integrating with an RGB-D camera, pressure sensing devices, etc. With a more comprehensive understanding of its surrounding, 7-DOF robot manipulators in the dual-arm robot system are more capable to reduce labor costs and improve operational efficiency in the near future.

V. Conclusion

This study presented an improved framework for human expert skill transferring in teleoperated dual-arm manipulation system. Unlike current approaches that directly send demonstration data to training models, this work matched human motion to robotic arm kinematic motion. However, the presence of noise often leads to unwanted vibration, hindering robots to perform human-like movements. A model-free solution presented in this work provided 60% of the accuracy improvement in human motion imitation, utilizing the EMD method and quadratic interpolation to eliminate unwanted noise and regenerate motor controllable trajectories. It could effectively denoise and reconstruct human delicate motion remotely with prior knowledge to manipulator model, making the deployment of dual-arm manipulation system more feasible and tangible in any kind of workspaces.

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VII. References

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