Identification of Rigid-Body Dynamics of Robotic Manipulators Using Type-2 Fuzzy Logic Filter

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***Abstract* - In this paper, a subtractive clustering based type-2 Takagi-Sugeno-Kang (TSK) fuzzy logic process is used as a fuzzy filter to treat acceleration data for the purpose of obtaining the rigid-body dynamical parameters of robotic manipulators. Experimental results show the effectiveness of this method, which not only provides good accuracy of prediction of the rigid-body dynamical parameters of robotic manipulators, but also assesses the uncertainties associated with the modeling process and with the outcome of the model itself. A comparison of the results from the type-2 fuzzy logic filtering algorithm with its type-1 counterpart is presented and limitation of those methods is discussed.**

I. INTRODUCTION

The past decades have seen increasing use of robotic manipulators to accomplish a wide range of tasks in a wide range of environments. In the industry, robots have been used for arc- and spot-welding, paint-spraying, die-casting, pick-and-place, assembly, and many other applications [1].

Robotic manipulators are complicated systems composed of a control system including its software and power electronics, as well as a complicated assembly of actuators and links. Among many research issues, a thorough understanding of its mechanics—in particular, its dynamics—is essential to the design and control of robotic manipulators. Derivation of the dynamic model of a robot is of uttermost importance to accurately simulate its motion. The analysis of robotic structures and design of control algorithms can also be significantly accelerated with the help of a dynamic model [2]. Simulating robot motions allows testing of control strategies and provides insight of motion planning techniques without the need of a physically available system. Computation of the forces and torques required for typical motions provides useful information when designing joints and transmissions or selecting actuators. Using a dynamic model to solve motion simulation and compute control inputs require the knowledge of the values of each dynamic parameter used in the robot model.

However, the dynamic parameters are not easily quantifiable. Standard industrial robot controllers do not use them and therefore, manufacturers usually do not provide them in their documentations. Moreover, design considerations may cause the links to exhibit complex shapes and to be composed of various parts. Hence, computing their values, even with a CAD software package can be impractical. It is technically possible to estimate the parameters by disassembling the robot to perform weighing, balancing, and pendulum tests on the individual parts [3]. Nevertheless, this approach can be impractical for certain robots and is very time-consuming.

In the mid-80's, significant contributions were made to the identification of dynamic parameters problem via the standard least-square technique, where the estimates of the parameters are computed from generalized force and motion data collected while the manipulator executes a trajectory [2]. One major difficulty in this technique is the need of differentiating the (noisy) signal from the joint position sensor to obtain velocities and accelerations that yields significant errors into the identification process. Moreover, many identification methods proposed in the literature were applied to industrial robots with geared transmission, which have significant unmodeled dynamics [4]. Because of the elasticity and backlash existing in these units, many industrial robots exhibit serious vibrational behaviour. Thus, a potentially significant amount of errors both in the data and the dynamic modeling might result in erroneous identification.

In this paper, accelerometers are used to estimate the joint velocities and accelerations. Since the robot has both rigid and flexible elements, it is necessary to extract the rigid-body dynamics component from the data in order to identify those inertial parameters. Therefore, the type-2 Takagi-Sugeno-Kang (TSK) fuzzy logic filtering algorithm is designed to not only filter out the vibrating components in the measurement data, but also obtain the uncertainties associated with the system, even the measurements. The information about uncertainties increases the credibility of assessments by explicitly describing the magnitude and direction of uncertainties, and providing the basis for efficient data collection or application of refined methods.

In the type-2 TSK identification algorithm [5], subtractive clustering method [6, 7] is combined with least- squares estimation algorithm to pre-identify a type-1 FLS from input/output data. Then using type-2 TSK FLS theory [8] expand the type-1 FLS to a type-2 TSK FLS. Minimum error models are obtained through enumerative search of optimum values for spreading percentage of cluster centres and consequent parameters.

This paper is divided into five sections. Section I contains the problem description and some introductory remarks. Section II recalls type-2 TSK FLS identification algorithm [5]. Section III introduces the experimental setup and acceleration measurements. Section IV includes experimental results and a comparison between the results from the type-2 fuzzy logic filtering algorithm with its type-1 counterpart and the traditional digital filtering techniques, also limitation of those methods and sources of uncertainties associated with the modeling system are discussed. Concluding remarks follow in Section V.

II. . Type-2 TSK Modeling Using Subtractive Clustering

The type-2 TSK FLS modeling algorithm [5], type-1 Gaussian membership functions (MFs) is an extension of the type-1 TSK FLS modeling algorithm proposed in [6, 7]. The proposed type-2 TSK modeling identification algorithm is as follow:

Step 1:

Use Chiu's subtractive clustering method [6, 7] combined with a least-squares estimation algorithm to pre-identify a type-1 fuzzy model from input/output data. For a multi-input single-output (MISO) first–order model, its *k*th rule can be expressed as:

IF x_1 *is* Q_{1k} and x_2 *is* Q_{2k} and … and x_n *is* Q_{nk},

THEN Z *is* $w^k = p_0^k + p_1^k x_1 + p_2^k x_2 + ... + p_n^k x_n$, (1)

where x_1, x_2, … , x_n and Z are linguistic variables; Q_{1k}, Q_{2k}, …, and Q_{nk} are type-1 fuzzy sets on universe of discourses X_1, X_2, …, and X_n and $p_0^k, p_1^k, p_2^k, ..., p_n^k$ are constant regression parameters.

MFs and number of rules of a type-1 TSK ssytem are identified by subtractive method, and the consequent parameters are identified by least squares estimation algorithm.

The *j*th MF is expressed as

$$Q_{jk} = \exp\left[-\frac{1}{2}\left(\frac{x_j - x_{jk}^*}{\sigma}\right)^2\right], \quad (2)$$

where x_{jk}^* is the *j*th input feature of *k*th cluster center, σ is the standard deviation of Gaussian MF, given as

$$\sigma = \sqrt{1/2\alpha} \quad (3)$$

with $\alpha = 4/r_a^2$ where r_a is the hypersphere cluster radius in data space which defines a neighborhood.

Step 2:

Calculate root-mean-square-error (RMSE) of the model. If RMSE is bigger than expected error limitation, go to Step 3. If not, end program, which means the type-1 model is acceptable, using a type-2 TSK model is not needed.

Step 3:

Use type-1 Gaussian MFs as principle MFs to expand type-1 TSK model to type-2 TSK model.

- spread cluster centre to expand premise MFs from type-1 fuzzy sets to type-2 fuzzy sets;
- different value assigned to the deviation of each variable in each rule;
- spread the parameters of consequence to expand consequent parameters from certain value to fuzzy numbers.

By doing so, a type-2 model is obtained. Equation (1) is transformed to (4), namely

IF x_1 *is* $\tilde{Q}_{1k}$ and x_2 *is* $\tilde{Q}_{2k}$ and … and x_n *is* $\tilde{Q}_{nk}$,

THEN Z *is* $\tilde{w}^k = \tilde{p}_0^k + \tilde{p}_1^k x_1 + \tilde{p}_2^k x_2 + ... + \tilde{p}_n^k x_n$, (4)

where $\tilde{w}^k$ output from the *k*th IF-THEN rule in a total of *M* rules FLS, $\tilde{Q}_{1k}$, $\tilde{Q}_{2k}$, …, $\tilde{Q}_{nk}$ are type-2 fuzzy sets. Moreover $\tilde{p}_0^k, \tilde{p}_1^k, ..., \tilde{p}_n^k$ are fuzzy numbers and the *j*th MF is expressed as

$$Q_{jk} = \exp\left[-\frac{1}{2}\left(\frac{x_j - x_{jk}^*\left(1 \pm a_j^k\right)}{\sigma_j^k}\right)^2\right], \quad (5)$$

where a_j^k is spread percentage of cluster centre x_{jk}^* as depicted in Fig.1, and σ_j^k is the deviation of *j*th variable in *k*th rule.

Furthermore

$$\tilde{p}_j^k = p_j^k (1 \pm b_j^k) \ , \quad (6)$$

where b_j^k is the spread percentage of fuzzy numbers $\tilde{p}_j^k$.

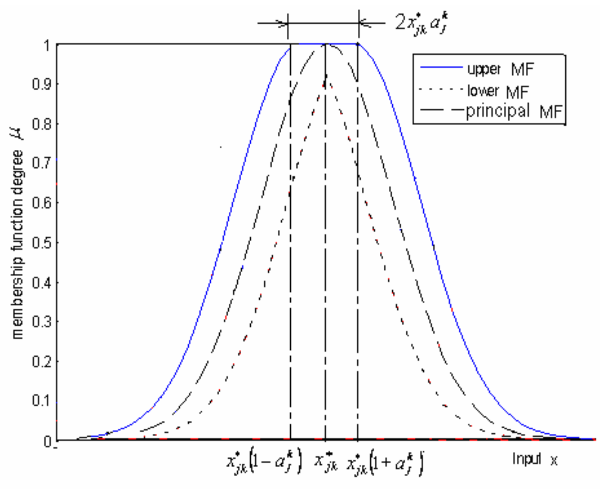

Fig. 1 Spread of cluster center

Step 4:

By using Mendel's interval type-2 TSK FLS computation method [2], obtain the interval value of the consequent for each input and obtaining the two end-points of output interval set and average value of output.

Step 5:

Calculate RMSE of this type-2 model. If RMSE is bigger than expected error limitation, go to Step3. If not, end program, which means a type-2 TSK model is obtained.

Minimum error models are obtained through enumerative search of optimum values for spreading percentage of cluster centres and consequent parameters because RMSE of the type-2 model is very sensitive to spreading percentage of cluster centres and the interval sets of output are very sensitive to spreading percentage of consequent parameters [9]. In this research, we are interested in both, the RMSE and interval sets of output.

III. Experimental Setup and Acceleration Measurements

For the purpose of dynamic parameter identification, we propose to estimate the joint velocities and accelerations from external sensing devices. A possible choice of technology for these devices consists in using inertial measurement units (IMUs), which estimate the linear and angular motions of a rigid body with respect to a fixed inertial frame. By attaching a unit to the end-effector of a robot, it is possible to estimate its angular velocity and acceleration, composed of all the relative motions between the connected links of the robot. If only one joint of the robot is moving while the others are locked, the IMU senses the angular velocity and acceleration of the moving links connected from this joint to the end-effector. In fact, the sensed motion data are nothing but the angular velocities and accelerations of the only actuated joint. These data should be more accurate than those obtained from differentiating joint positions, and consequently, better parameter estimation can be achieved.

The compliance of the driving systems must be considered when using external measurements. In many electric-powered robots, each joint is driven through a reduction gear such as harmonic drive. Therefore, the external sensors are measuring the motion resulting from both rigid-body dynamics and flexibility in the transmission.

As shown in Fig. 2, the CRS plus A-460 robot is employed for the experimental verification of the proposed method. It is a small, six degrees of freedom (DOF) robot manufactured by CRS Plus Inc. of Burlington, Canada. Its main industrial use is for automation of light industrial tasks such as small parts assembly, inspection and quality control. The first joint of the robot is used to provide the angular motion for our acceleration measurements. In an electric-powered robot, each joint is driven through a reduction gear such as harmonic drive. Therefore, the external sensors are measuring the motion resulting from both rigid-body dynamics and flexibility in the transmission.

Fig. 2 CRS plus A-460 manipulator.

An experiment with a simple configuration of the robot is used to illustrate the data acquisition and processing procedure. In this case, only the first joint of the CRS robot is moved while others are locked. Thus the kinematic model can be simplified to a single DOF mechanism as displayed in Fig. 3. Therein, two accelerometers are placed on the end-effector in order to measure the accelerations of two points along orthogonal directions. The arrows drawn on Fig. 3 denote the direction of the acceleration being sensed. If the joint and the link are rigid, the measured accelerations are related to the angular velocity and acceleration as

$$a_1 = \ddot{\theta} r_1 \quad (7)$$

$$a_2 = \dot{\theta}^2 r_2 \quad (8)$$

where, a_1 and a_2 are the measured accelerations of accelerometer 1 and 2, respectively; $\dot{\theta}$ and $\ddot{\theta}$ are joint velocity and acceleration; and r_1 and r_2 denote the distances from the accelerometer 1 and 2 to the joint axis.

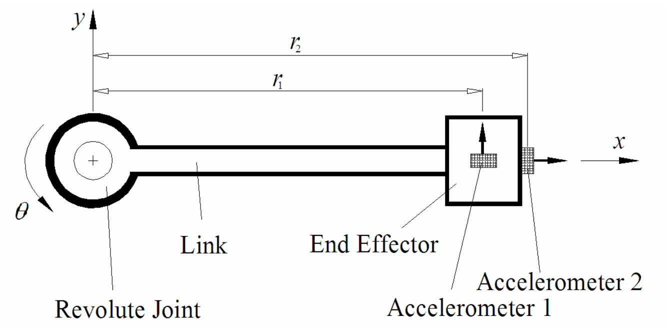

Fig. 3 One joint mechanism

In our experimental setup, the joint is programmed to perform a trapezoidal velocity motion: first, constant acceleration; then constant velocity; last, constant deceleration. Meantime, real-time data are acquired from the two accelerometers by means of data acquisition hardware. Then a data filtering algorithm is used to analyze the data and classify the results in order to make a reliable estimation of joint velocity and acceleration. Fig. 4 and Fig. 5 show the acceleration measurements from the two accelerometers. There are significant vibrations observed from the acceleration signal in them. This demonstrates the necessity to design a proper filtering process to eliminate the vibrating component from the data in order to identify the rigid-body dynamics of the manipulator.

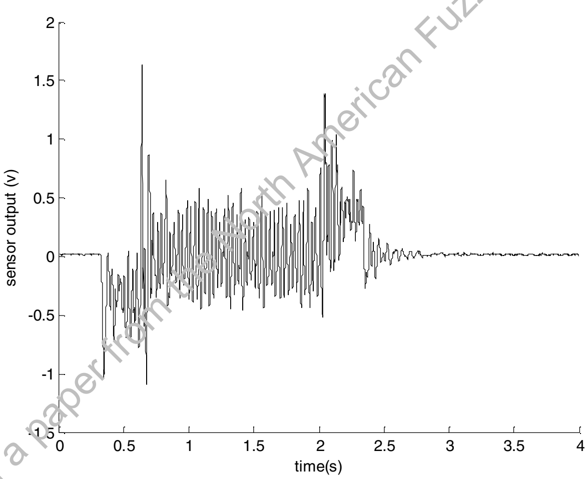

Fig. 4 The acceleration measurement from accelerometer 1

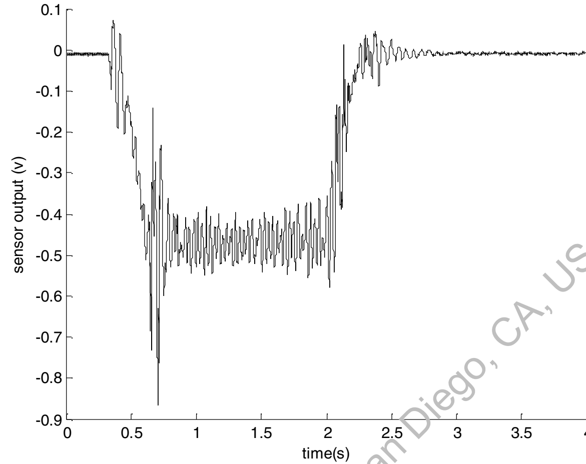

Fig. 5 The acceleration measurement from accelerometer 2

IV. Data Processing

A. Data Filtering

As shown in Fig. 6, the part of the data from accelerometer 2 is processed by the designed type-2 fuzzy logic filter to demonstrate its effectiveness.

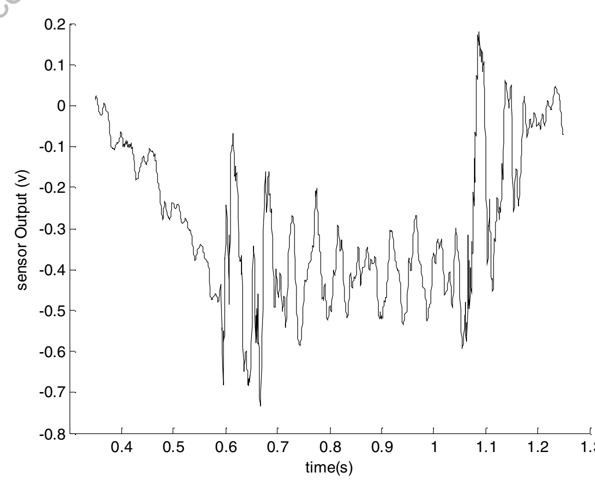

Fig. 6 Experimental data

By using our type-2 TSK fuzzy logic identification algorithm described in Section II, a 7 rules type-2 TSK fuzzy logic filter is obtained to filter noise in the experimental data. The membership functions of the fuzzy system are shown in Fig. 7.

Figure 8 indicates the system output information: sensor output, output of pre-identified type-1 system and the three outputs of type-2 system: average output, upper output and lower output. Comparing with type-1 FLS, the type-2 FLS provides more information, not only crisp output (average output) as that of type-1 TSK FLS, but also the interval set of the output. This interval set of the output (the area between the upper output and lower output) has the information about the uncertainties that are associated with the crisp output, and this information can only be obtained by working with type-2 TSK FLS.

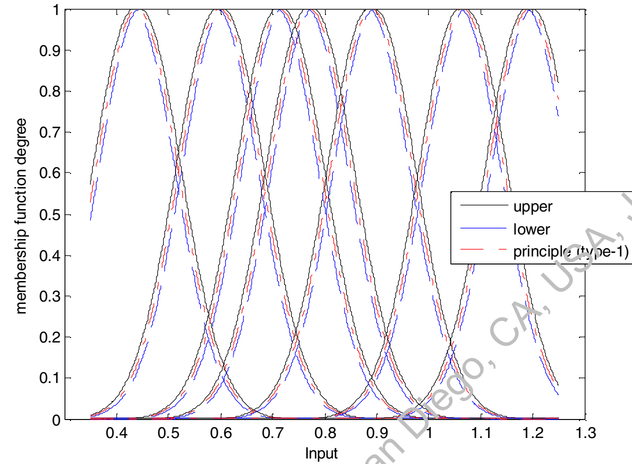

Fig. 7 Type-2 membership functions

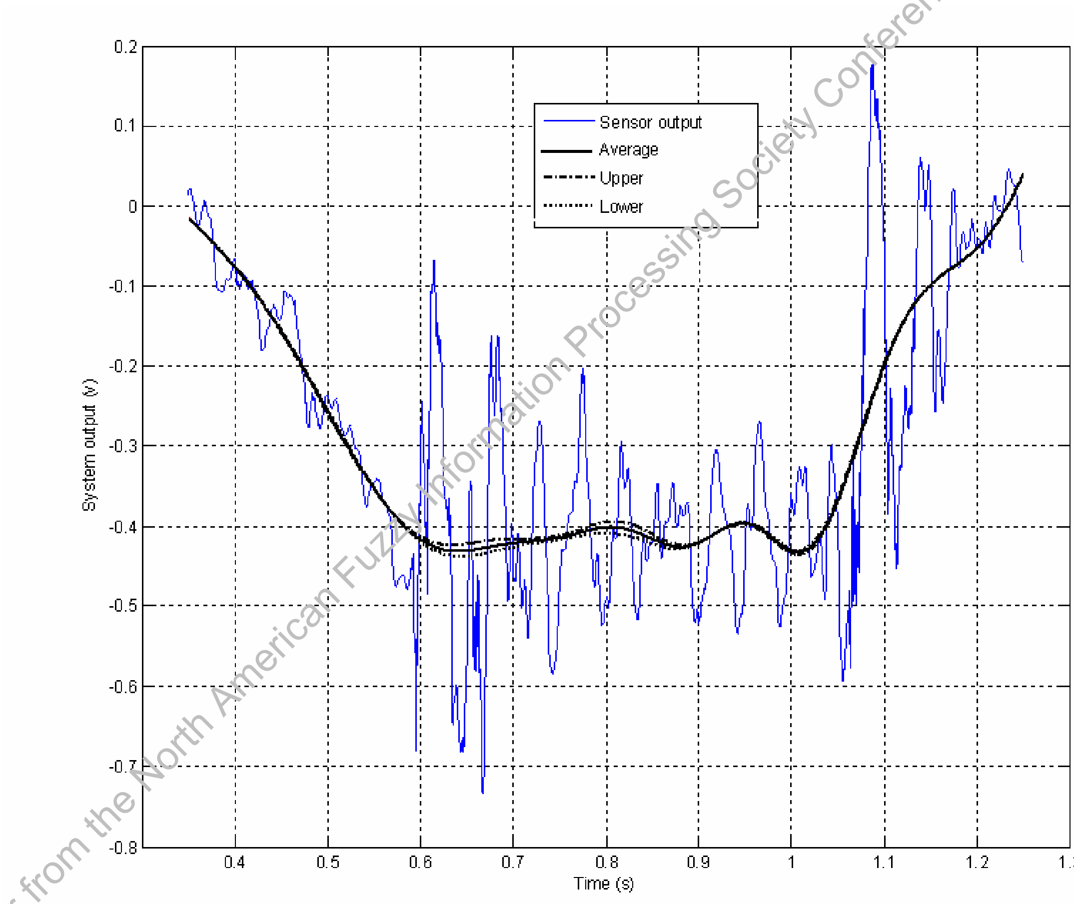

Fig. 8 Type-2 fuzzy logic filtering

B. *Sources of Uncertainties*

There are several possible sources of uncertainties associated with this technique:

- Uncertainties from the robot itself: the structural compliance of the links, joints and drive components of the robot results in the oscillatory behaviour of the robot link motion and the driving torque profile.

- Uncertainties from the sensors: sensitivity to the environment change such as temperature and humidity, the circuit noise, the locating error of the sensors, and etc.
- Uncertainties from data processing system – the type-2 TSK filtering algorithm, because of need of identification of the spreading parameters.

IV. Conclusion

This paper proposes a type-2 TSK fuzzy logic filter, which can be used to treat acceleration measurement data for the purpose of obtaining the rigid-body dynamical parameters of robotic manipulators. Experimental results show that this filter not only provides good prediction of the rigid-body dynamics of robotic manipulators, but also can assesses the uncertainties associated with the modelling process and the outcome of the model itself. Since the dynamics of industrial robotic manipulators is space and time dependent, an adaptive type-2 fuzzy logic filter needs to be developed in order to cope with this situation.

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