ON-LINE SENSING AND MODELING OF MECHANICAL IMPEDANCE IN ROBOTIC FOOD PROCESSING

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Abstract

Measurement of mechanical impedance is useful in robotic food processing. In cutting meat, fish, and other inhomogeneous objects by means of a robotic cutter, for instance, it is useful to sense the transition regions between soft meat, hard meat, fat, skin, and bone. Product quality and yield can be improved through this, by accurately separating the desired product from the parts that should be discarded. Mechanical impedance at the cutter-object interface is known to provide the necessary information for this purpose. Unfortunately, the conventional methods of measuring mechanical impedance require sensing of both force and velocity simultaneously. Instrumenting a robotic end-effector for these measurements can make the cutter unit unsatisfactorily heavy, sluggish, and costly. An approach for on-line sensing of mechanical impedance, using the current of the cutter motor and the displacement (depth of cut) of the cutter, has been developed by us. A digital filter computes the mechanical impedance on this basis. For model-based estimation, performance evaluation of the on-line sensor, and also for model-based cutter control, it is useful to develop a model of the cutter-object interface. This paper illustrates these concepts using a laboratory system consisting of a robotic gripper and a flexible object. The prototype consists of an industrial-quality robotic gripper, a control computer, and associated hardware and software for data acquisition and processing. A model of the process interface between the end-effector and object has been developed. Some illustrative results from laboratory experiments are given.

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1. INTRODUCTION

When processing inhomogeneous material, which is a common situation in the food processing industry, it is desirable to detect the transition regions within the material. This will be crucial in improving the yield and product quality. For example, consider the case of removing the head from the body of a fish. If the useful meat is removed with the head, the yield and revenues will suffer and a useful natural resource will be wasted. If parts of the head are left behind with the body, the product quality and aesthetic appeal will degrade, and furthermore, an additional effort will be needed to remove the unwanted parts [2]. Consider a robotic fish processing operation, as schematically shown in Figure 1.

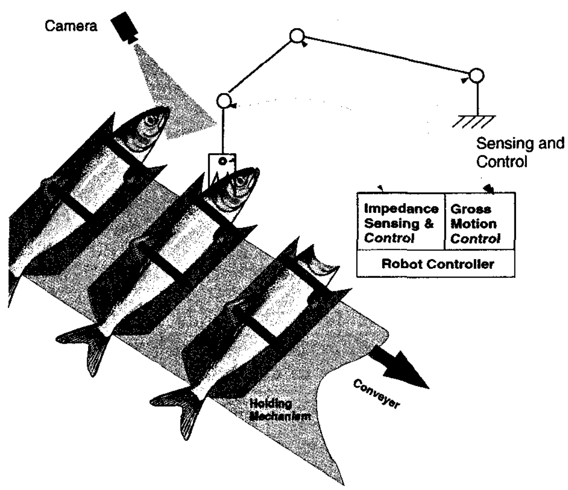


Figure 1: Schematic Representation of a Robotic Fish Processing Operation

It is neither convenient nor economical to instrument the fish to determine various regins such as skin, bone, and useful meat within its body. A better approach would be to determine these regions on line as the cutter interacts with the fish, perhaps with the assistance of high-level sensors such as "intelligent" vision. On-line sensing is desirable not only for ascertaining the characteristics of the object that is being processed, but also in controlling the process operation. For example, motion sensing is particularly important in controlling gross manipulation tasks involving robots. When slight errors in motion could generate large forces/torques, force sensing would be needed for proper control of the process. Force sensing alone may produce noisy and high-frequency signals, and besides, may lead to unstable behavior when used in control, in the absence of motion feedback loops [1]. A hybrid approach of impedance sensing, where mechanical impedance is defined as the ratio: Generalized Force/Velocity, when used in control, may provide stability of motion control and the precision of force control, with an added degree of flexibility [1].

Sensing of mechanical impedance will provide a means of on-line characterization of the object-cutter interface. This may serve as a gradient measure, for example, which will be employed to steer the cutter either towards or away from certain regions. Furthermore, as illustrated in [1], an impedance control policy may be developed whereby the process impedance may be adjusted so as to optimize an appropriate performance index. In this manner impedance control may be viewed as a case of optimal control as well. The direct way to sense mechanical impedance is through simultaneous measurement of force and velocity at the process interface. Since an explicit force sensor will increase the mass and also the instrumentation cost of the end effector, it is proposed in the present paper that motor current be used to estimate the force parameters. Also, without using an explicit velocity sensor, a built-in optical encoder will be employed. The sensory signals obtained in this manner may not represent the desired variables, for reasons such as dynamic interference, external disturbance, and noise. The measurements have to be conditioned and further processed for on-line estimation of mechanical impedance at the interface of the object and the end effector. This procedure may be assisted by a dynamic model of the process interface. The same model may be useful in performance evaluation and model-based control as well. Furthermore, the low-level information may be preprocessed and used in a high-level supervisory control systems for the process, with assistance from other sensory means such as vision. The paper will describe these various aspects of impedance sensing for process control. Preliminary results obtained from a laboratory prototype that has been developed, will be presented.

2. THE LABORATORY PROTOTYPE

In the preliminary version of the laboratory prototype, instead of using a robotic cutter interacting with an object, a robotic gripper is interacted. This will provide a cleaner system, and furthermore, process instrumentation for data acquisition becomes simpler. Once the techniques are validated for the gripper system, the same approaches may be extended to a robotic cutter system.

Figure 2 shows a photograph of the laboratory system (part). The laboratory prototype consists of a

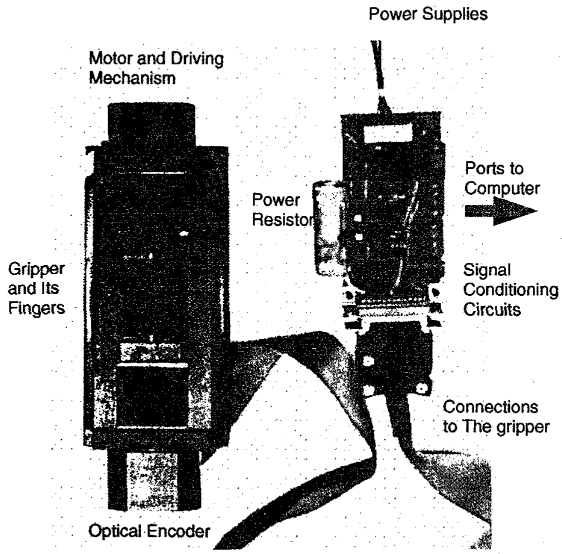


Figure 2: System Setup

commercially available gripper (Model SEG-10, manufactured by Schunk), which has two fingers that are driven by a brushless four-quadrant servo motor with PWM amplifier. The gripper also has a built-in encoder of resolution 500 pulses/rev. A PC-486 computer with analog-to-digital converter (ADC), digital-to-analog converter (DAC) and encoder cards is used for data acquisition and control. An electric circuit has been built to measure the drive-motor current. The current signal and the finger position signal are sent to the ADC and the encoder card, respectively. Various control schemes, including impedance control, may be implemented within the control computer. At present, only a motion feedback scheme is present, so as to facilitate gripper operation. This will be enhanced with other control schemes once the estimation of mechanical impedance is perfected. Control signal from the computer is sent to the drive circuitry of the gripper through a DAC card (see Figure 3).

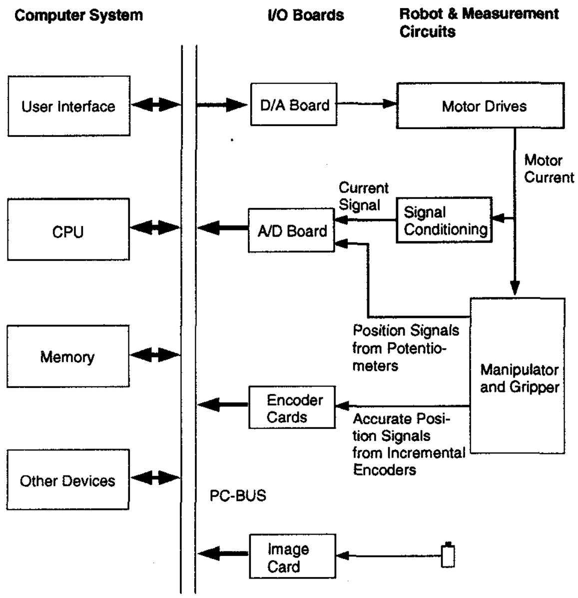


Figure 3: The System Configuration

In the present system, the motor current is measured by the voltage drop across a small resistor that is connected in series with the motor. This resistor may degrade the motor performance during operation, particularly when a high torque is required. A better sensor, such as Hall effect element, may be used in a future development. The velocity is estimated from the position signal which is accurately measured by the optical encoder. Mechanical impedance at the object-gripper interface, is a function of motor current (i), finger velocity (v), gripper friction (F_f), and system inertia mass (m).

$$z_i(t) = g(i(t), v(t), F_f(t), m)$$

where z_i denotes the interface impedance, and g is a nonlinear function. Note that the motor current represents the force generated by the drive-motor. But, the system inertia will affect the force applied to the object. However, when friction and dynamic effects are small, and by neglecting external disturbances and signal noise, a rough estimate for the mechanical impedance is given by the ratio of current to velocity. This has been verified in the preliminary experiments with a simplified object, at low speed.

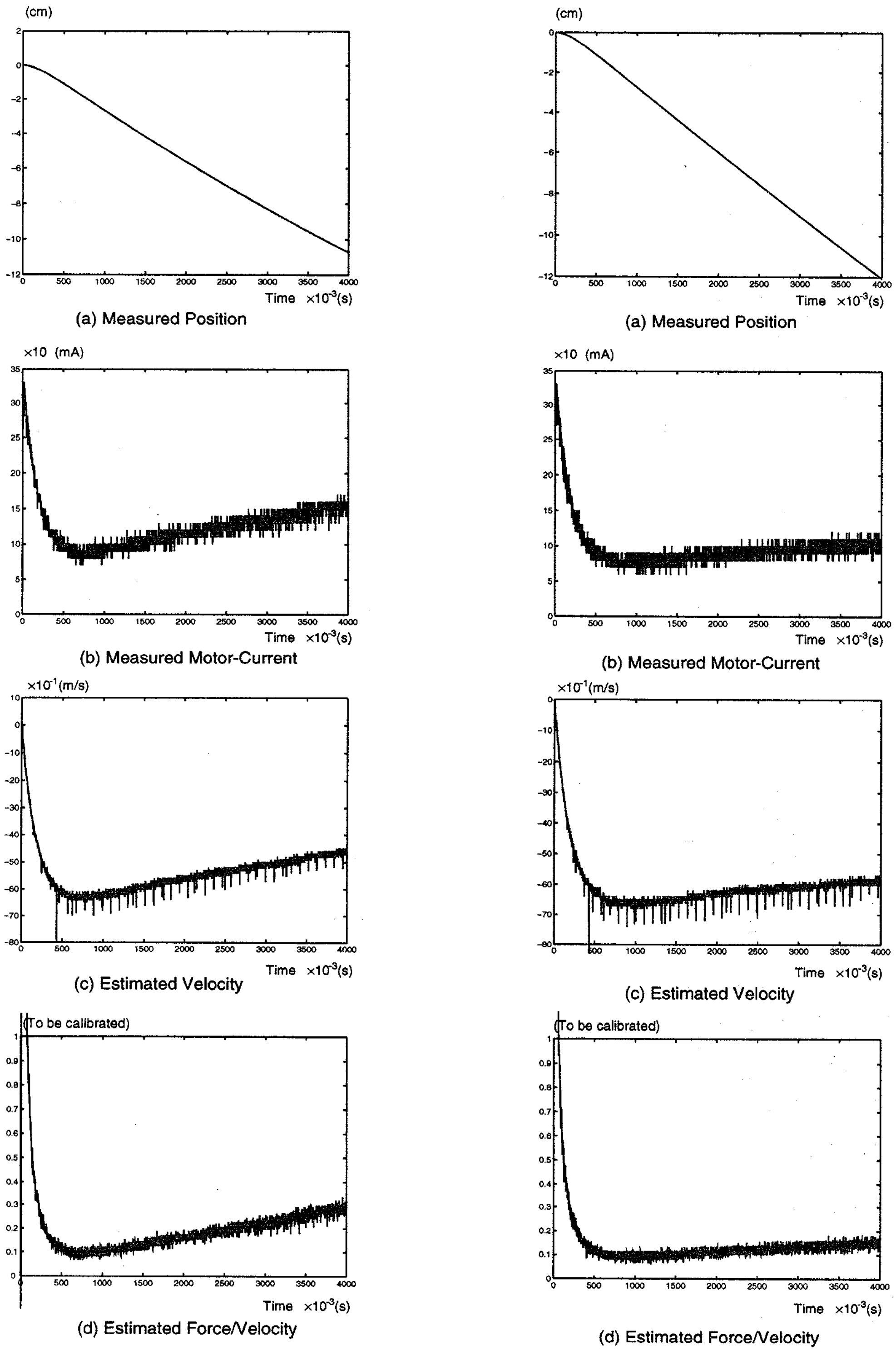
In the initial experiments, a spring with its ends attached to the gripper fingers, is employed as the process object. The load on the gripper is gradually varied by moving the fingers of the gripper, under motion control. A representative set of experimental results for finger position and motor current is given in Figure 4 (a) and (b), for a stiff object (case I) and a soft object (case II). The profiles of velocity and impedance, as estimated from these signals are shown in Figure 4 (c) and (d), for these two types of objects.

Two cases emulate a high-impedance process and a low-impedance process, by selecting the spring parameters appropriately. Here, velocity was obtained by digital differentiation, and the mechanical impedance was estimated as the ratio of current to velocity. Clearly, the motor current signal is quite noisy, and so is the estimated velocity. They are not suitable in the present form for use in fine manipulation and mechanical processing. However, the estimated force/velocity approximates the applied impedance (provided by the spring), except in the initial part which is corrupted by gripper dynamics and start-up noise. Particularly, a higher impedance is experienced in case I than in case II, as expected. For better results, improvements should be considered in several aspects; for example,

- Use of a better sensor for current sensing; and a high-resolution ADC for accurate quantization;
- Development of high quality digital filters [5] for accurate processing of the sensory signals;
- Development of a Kalman filter [7] to estimate velocity instead of using direct differentiation which is known to enhance noise;
- Accurate estimation of mechanical impedance by eliminating the influences of gripper dynamics, system friction, and other disturbances and noise.

3. MODEL DEVELOPMENT

A process model may be useful in the present application, in several ways. First, in estimating the mechanical impedance using the measured signals, one could use a digital filter/estimator based on the model, with the measured signals as inputs, and the impedance as the estimated output. Second, a model may be a reference, based on which the actual performance of the process could be evaluated. In this respect, the reference model may serve the purpose of a performance specifier. Third, a model will be needed in model-based control of the process. Again, the model could be either an approximate model of the true process or a reference model toward which the process is driven.



(Case I: High Stiffness)

(Case II: Low Stiffness)

Figure 4: The Results of Measurement and Estimation

In the present project, initially, a robotic gripping operation is employed to validate the developed technology. Subsequently, a more appropriate process of cutting will be used to apply the developed technology. Single-degree-of-freedom (DF) grippers, such as the one employed in the present project, are widely used in robot manipulation. A model is developed for the robotic gripping process, first for use in the estimation of mechanical impedance. Generally, a model for a single-DF actuator interacting with an object can be separated into the actuator part and object-environment, with a common through-variable: velocity at the interface between end-effector and object. The following factors should be taken into consideration: characteristics of driving force/torque which is usually generated by a DC motor; inertia of moving parts; and energy dissipation in the system (e.g., friction). The model (see Figure 5) may be expressed in a general form as:

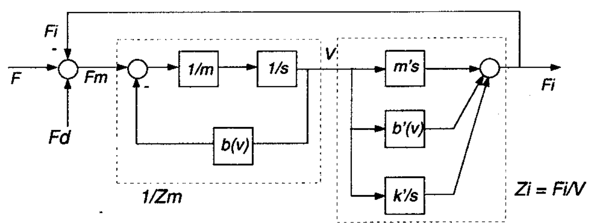


Figure 5: A System Model

$$F - F_i - F_d = Z_m V \tag{1}$$

and

$$F_i = Z_i V \tag{2}$$

where F= force/torque generated by the actuator (motor); F_i= force at the interface between end-effector and object; F_d= process disturbance; Z_m= impedance of the end-effector including motor rotator, transmission system and gripper fingers; Z_i= impedance of the object at the interface between end-effector and object; V= velocity at the interface. Note that the electric time constant of the motor circuit is very small compared to the mechanical inertia delay, and is neglected [1]. The main task is to estimate the impedance at the process interface Z_i.

$$Z_i = \frac{F_i}{V} \tag{3}$$

Here F_i can be estimated from equation (1), and V can be estimated from displacement of the gripper fingers. Note that F_d which includes Coulomb friction, should be taken into consideration in estimating F_i. [4].

In Figure 5, the end-effector is considered as a rigid body. Otherwise, stiffness of the end-effector should not be ignored. The three common types of object and environment are:

1. inertial type impedance, $Z_i = m's$;
2. resistive type impedance, $Z_i = b'$; and,
3. capacitive type impedance, $Z_i = \frac{k'}{s}$.

Here Z_i is the impedance expressed in the frequency domain (s domain); m', b', and k' are parameters of the object/environment model (see Figure 5).

Usually, an impedance model of object/environment consists of a combination of the three types. One or two of them may be neglected under certain condition. For example, in fish cutting, where the object (fish) is usually fixed during the cutting process, the inertial impedance may be overlooked, resulting in a model consisting of resistive and capacitive impedances alone.

The model (Figure 5) may not be an exact representation of the process, and will contain many unknowns, as primarily represented by F_d. Now, a digital filter of the Kalman type [6] may be incorporated with this model, to obtain on-line estimates of mechanical impedance. Specifically, the measured signals (motor current and gripper displacement) will form inputs to the filter/estimator and the mechanical impedance of the process interface, as modeled, will be its output (estimate). The estimate is thought to be accurate when the model response matches the response of the actual process. This work is in progress.

4. HIERARCHICAL SUPERVISORY SYSTEM

The control system of the process will take a hierarchical structure [3]. This is represented in Figure 6. Direct control of the process is carried out at the lowest level, using low-level sensory information including mechanical impedance at the process interface. Servo control, impedance control, and other direct control techniques may be implemented in this layer, as appropriate. The intermediate layer performs signal preprocessing, filtering, information fusion, and interpretation functions. The top layer is the the most "intelligent" module of the control system. It performs monitoring and supervisory control operations, at a relatively low bandwidth, using preprocessed sensory information from the lower layers. High-level vision may be employed here, to assist the low-level sensors, in carrying out the high-level supervisory control tasks. Typically, the top layer of the control system

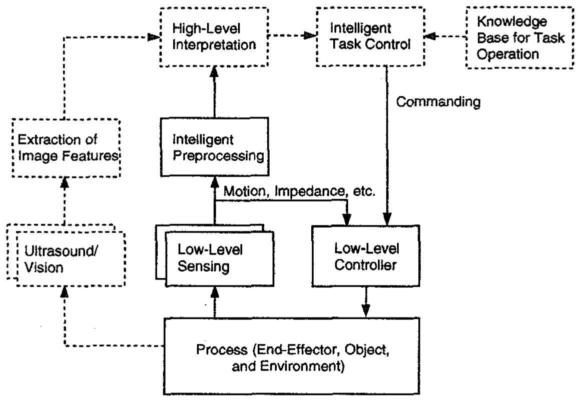


Figure 6: System Architecture

will consist of a knowledge base and a reasoning mechanism, which are triggered by the sensory information. An operator interface is also available for this level, for external intervention.

5. CONCLUSION

The mechanical impedance approach is particularly useful in fine manipulation and processing tasks involving robots. Dynamic effects may be negligible in this domain, while material properties and other physical phenomena such as flexibility and dissipation, which are nonlinear in general, become crucial. Some preliminary concepts in formulating the associated problem were established. Experimental results for determining impedance using motor current and displacement of a robotic gripper, were presented. A single-degree-of-freedom model that would be useful for purposes such as impedance estimation, control, and performance evaluation, was given. A criterion will be developed for separating the domains of fine and gross manipulation. The process model will be enhanced, and techniques will be developed based on the model, for process control and performance evaluation. The on-line impedance sensor will be further developed, tested, and implemented on a robotic food processing task.

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REFERENCES

[1] De Silva, C.W., *Control Sensors and Actuators*, Prentice Hall, Inc., Englewood Cliffs, NJ, 1989.

[2] De Silva, C.W., "Research Laboratory for Fish Processing Automation", *International Journal of Robotics and Computer-Integrated Manufacturing*, Vol. 9, No. 1, pp. 49-60, 1992.

[3] De Silva C.W., *Intelligent Control: Fuzzy Logic Applications*, CRC Press, Boca Raton, FL, 1995.

[4] Haessig, D.A. Jr., and B. Friedland, "On the Modeling and Simulation of Friction", *ASME J. Dynamic Systems, Measurement, and Control*, Vol. 113, Sep., pp. 354, 1991.

[5] Jackson, L.B., *Digital Filters and Signal Processing*, Kluwer Academic, Boston, 1989.

[6] Lewis, F.L., *Optimal Estimation*, John Wiley and Sons, New York, 1986.

[7] Lewis, F.L., *Applied Optimal Control and Estimation: Digital Design and Implementation.* Prentice Hall, Englewood Cliff, NJ, 1992.