Recognition and Modeling of Smart Sensor Integration on Robotic Control Application

Zhengmao Ye, *Member, IEEE* and Gregory Auner, *Member, IEEE*

***Abstract*--Multisensor integration is the synergistic application of different types of sensors. Robotics is a popular research discipline on multisensor integration. Various sensors are employed for robot manipulations, such as vision, force, temperature, ultrasound, acoustic wave, and so on. This research addresses the recognition and modeling of the multisensor integration for the medical robot application, which is a remarkable step for the actual robot operation on the human body. Simplified dynamics models about robotic smart sensor applications are given based on the essential aspects of mechanical, electrical, visual and thermal characteristics. The robotic integration strategy is presented in terms of the robotic multiple sensor modeling. A model reference control scheme is proposed to achieve the satisfied robot performance.**

***Index Terms*--Robot sensing systems, Object recognition, Modeling, Feedback, Force control**

I. Introduction

Multisensor integration has many applications including robotic control, automotive control, military surveillance, space control, pattern recognition, target tracking, alarm analysis, medicine and finance, and so on. Most work on object recognition and parameter identification can be performed together by a variety of sensors in different environments, such as vision, touch, laser, and so on. Target tracking used in military and defense seeks to combine various observed data from multiple sensors. Multisensor fusion in medicine is to combine multisensor measurements and deduce more accurate assessment of the human body conditions so as to diagnose ailments. Sensor fusion has also been used for alarm analysis by fusing visible, infrared and millimeter wave radar data. Robotic operation by the individual visual information often confronts with difficulties because of occlusions caused by the actual object, by surrounding objects and by the manipulator itself. Additional information, such as touch, force, grasp, vibration can provide complementary information to aid in optimal operations.

The authors are with the Department of Electrical and Computer Engineering , Wayne State University, Detroit, MI 48202, USA (email: yzm@ece.eng.wayne.edu and gauner@ece.eng.wayne.edu)

Multisensor integration is classified into multisensor data fusion, multisensor planing and multisensor architecture. Multisensor fusion deals with the fusion from sensory information of multiple sensors into a common format. Miscellaneous multisensor data fusion has been applied to many applications. Multisensor planning is about the acquisition of sensor data such as deciding what data to acquire and how to acquire it. Multisensor architecture is used for control design and data flow in a multisensor system to achieve the maximum benefit by coordination and the robustness. The benefits for the multisensor data fusion include accuracy, synergy, reliability, robustness and efficiency. Registration scheme and fusion scheme are two essential issues for multisensor data fusion. Registration is the process of aligning sensor reference frames. Calibration errors must be considered during registration process. Once sensors are registered, data features in one sensor should associate the same aspect of the environment with the other sensors, which is a data association problem. Environment model refers to the explicit or implicit representation of the subject under observation by various sensors. The important model selection issues for the multisensor fusion include the environment model selection, model parameterization and data selection. Sensor modeling refers to the utilization and design of sensor and the related sensing data models.

Data from different sensors ought to be converted into a common reference frame prior to combinations. Fusion schemes should be able to handle both homogeneous and heterogeneous data features from different types of sensors. Redundant data can be exploited from some competitive sensors to reduce the uncertainty in fusion inference. Multiple time scales and time varying data should be incorporated in the fusion method. The measurements from different sensors are to some degree independent. A measurement from certain sensor might provide others with more information to improve measurement accuracy. On the other hand, information from multisensor system is not totally independent since sensors operate in the close vicinity and are subject to the same aspect of environment disturbances. Observations by different sensors are somewhat redundant. Improper modeling may result in less informative and sensors tend to overestimate the importance of some aspects. A data fusion algorithm ought to minimize the impact of sensor dependence. Object overlapping is a common problem encountered in sensory identification and recognition. Accuracy should be high enough to identify objects and to locate its position and orientation. An image with overlapping objects is difficult to analyze since its contour information requires a careful interpretation. Multiple sensor fusion can be used for model based object recognition. A model should be adequate which follows the sensing mechanisms. Multiple sensor system can extract both global features (perimeter, area, density) and local features (segment, line, vertex, edge) within the entire object boundary. A matching process between the object model and the feature depends on the completed feature extraction [1-3].

Feedback control design has a significant impact on the quality of robot control applications. Robotic feedback control systems are to improve the operation precision and dexterity. For example, advanced visual feedback control design increases the sensing transparency and the realism of the simulation. Advanced force feedback can provide feedback information by surface deformations, contact forces and surface constraints. Visual feedback provides information over a relatively larger area of the workspace without environment contact. Force feedback provides highly localized and precise information upon contact. The ultimate aim for the combination of force and vision is to enable the operators to obtain enough critical information as they operate. To coordinate the controllers based on multiple sensors, schemes have to be associated in one common coordinate frame. It is necessary to coordinate the robot end-effector control schemes by tactile feedback, visual feedback, touch force feedback or possible temperature feedback. The control designs such as hybrid control and adaptive control systems have been presented by hybrid structure of sensor based controllers, which can effectively eliminate the system errors [4-7].

Various identification and control methodologies have been applied to robotic multisensor integration. Kalman filter and Bayesian method can be employed for signal and image processing. Hopfield network is proposed to communicate between object features and data features. Gaussian Markov estimation and extended Kalman filter have been used for feature extraction. Energy minimization and least square estimations are solutions for data fusion estimation. Maximum likelihood method deals with the statistical data inference. Entropy based methods are applied for information analysis. Fuzzy logic and neural network have been applied to solve data interpretation problems [8-14].

In this research, the sensory information from camera, ultrasound, force sensor, tactile sensor, acoustic wave sensor, Raman spectroscopy and infrared spectroscopy is proposed as the feedback or feedforward information to improve the robotic enhanced medical operation. The simplified sensor models are given and model reference adaptive control scheme is then proposed to coordinate the integrated system.

II. System Configuration

The medical robot system and its virtual environment are two major elements in this research. The robot has three arms and one arm with a stereoscopic camera is to take 3D images. Ultrasound probe can be placed around the end-effector for enhancing the 3D visual effect. Acoustic wave sensor or a testable flexiforce sensor attaches the object surface to measure the touch force. Both the visual and haptic sensing information will be captured by the computer controlled system. Operators view the visual image and sense the actuated tactile forces through the vibration tactile sensors. Raman spectroscopy or infrared spectroscopy is to recognize sample tissues by analyzing the spectrum signature. It can be attached to the end-effector using a probe. The configuration of the robotic integrated sensing system is shown in Figure 1.

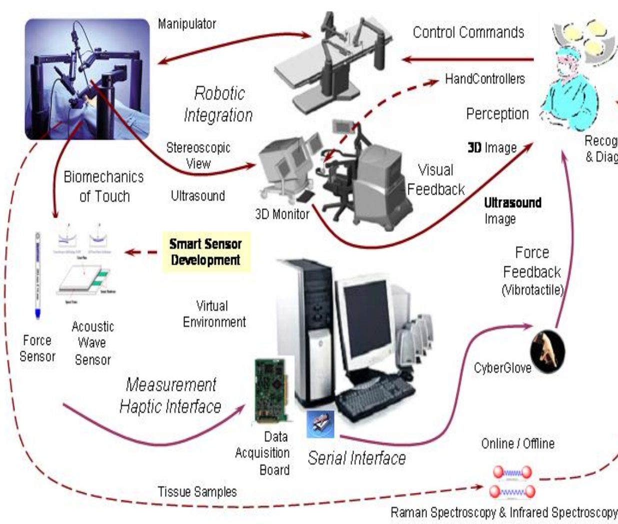

Figure 1 Configuration of Robotic Sensory Integration

III. System Recognition And Modeling

A. Robot Manipulator Dynamics Model

The well-known dynamics of a serial n-link ($n \le 6$) robot manipulator is formulated as:

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) = \tau \qquad (1)$$

where q (n×1) is the joint displacement vector to the base coordination system, τ (n×1) is the joint torque vector, M(q)(n×n) is the symmetric positive definite manipulator inertial matrix, $C(q,\dot{q})\dot{q}$ (n×1) is the vector representing both the centrifugal effect and Coriolis effect, G(e) (n×1) is gravity term vector. Now the state equation of robot dynamics model can be derived as:

$$\frac{d}{dt}\begin{bmatrix} q \\ \dot{q} \end{bmatrix} = \begin{bmatrix} \dot{q} \\ -M^{-1}(C\dot{q} + \mathrm{G}) \end{bmatrix} + \begin{bmatrix} 0 \\ M^{-1} \end{bmatrix}\tau \tag{2}$$

The robotic control law is to find a satisfied torque u = τ to achieve the desired motion.

B. Object Coordination Model

The sensor integration requires for a common or a global frame of reference. An object model in a global reference frame ought to be mapped into local sensor measurement frame to express the observed data. The object model is characterized by the position and orientation parameters. The object (tissue) has m_1 ($m_1 \leq 6$) degrees of freedom (DOF). Let Z ($m_1 \times 1$) be the generalized coordinates that represent the object position. The object motion model can be formulated as:

$$\dot{Z} = J_o(p)\,\dot{p} \tag{3}$$

where $J_o(m_1 \times m_2)$ is a velocity transformation matrix and the vector p ($m_2 \times 1$) is the actual position parameter with respect to the base coordinate system. This simple model can be easily extended to a larger motion pattern set.

C. Touch Force Sensor & Tactile Sensor Model

The touch force sensor data are regarded as imposing constraints on object surfaces. Subjects of force control include the contact force, stress, strain, displacement, and the surface deformation within a contact area. Excessive contact force should be avoided.

Assume the object manipulated by a medical robot is the body tissue with certain mass (m). The elasticity of the body tissue is analogue to the damping coefficient (b) of a damper. The thin film touch force or tactile sensor can be viewed as a spring with stiffness (k). When a normal stress is impressed on the body tissue and the attached sensors, it can be simply regarded as the spring-damper system. The dynamic model is written as:

$$m\ddot{y} + b\,\dot{y} + k\,y = F_T \tag{4}$$

where y is the deformation of the object and F_T is the touch force. The state equation of touch force sensor model is then formulated as:

$$\frac{d}{dt}\begin{bmatrix} y \\ \dot{y} \end{bmatrix} = \begin{bmatrix} \dot{y} \\ -\frac{b}{m}\dot{y} - \frac{\mathrm{k}}{\mathrm{m}}\mathrm{y} \end{bmatrix} + \begin{bmatrix} 0 \\ \frac{1}{m} \end{bmatrix} \mathrm{F_T} \tag{5}$$

The thin film force sensor can measure both static force and dynamic force between two surfaces and it acts as a resistor. When multiple touch force sensors are present, the dynamics model and state equation can be obtained by substituting the single variable with multiple variable vector term. The mechanism of tactile sensors is similar. Tactile sensors can provide high-accuracy robotic wrist, joint and angle measurements by resistive sensing technology (bend, flexion or abduction) to transform robotic motions into real time joint and angle data accurately. Dynamic model has the similar formulation in a vector form. The tactile data registration depends critically on kinematic calibrations of the robot system. For tactile sensors, relationship between contact points and object surface is many to one mapping, several contact points correspond to one object surface.

D. Acoustic Wave Sensor Model

An alternative approach for force measurement is to use acoustic wave sensors. Its model can be estimated by the principle of the reverse piezoelectric effect. The acoustic wave sensor has the merits of high sensitivity, good linearity and low hysteresis as well as a wide versatility with numerous applications. Its wave propagation is entirely a mechanical phenomenon. When an alternating voltage is applied to the surface of piezoelectric crystal, the material between the electrode patterns distorts due to the piezoelectric effect. This periodic deformation gives rise to the acoustic wave propagation with the frequency f. Vibrating crystal behaves as a harmonic oscillator at resonant frequency. The resonant frequency induces maximum displacement of the crystal surface. By the reverse piezoelectric effect, the acoustic wave can be detected at the other end of the substrate. Its mechanism is analogue to RC circuits with equivalent resistance and capacitance (R, C). The generated electric charge is expressed as:

$$Q = k\,F_A\sin(2\pi ft) = q_1 + q_2 \tag{6}$$

where k is a coefficient, $F_A\sin(2\pi ft)$ is the force on the crystal surface. q_1 is the part to charge the capacitor and q_2 is the part being converted into thermal energy by the resistor. Let u be the voltage drop across the crystal. After taking the time derivative on both sides of this equation, we have:

$$(RC)\dot{u} + u = (2\pi fk)\cos(2\pi ft)\,F_A \tag{7}$$

which is the dynamic model of the acoustic wave sensor. It is a first order system, which is simpler than a second order system such as touch force sensor or tactile sensor.

E. Camera Feature Transformation Model

Object images are generated by perspective projections of the relative position between the camera and the object. The object registration relies on good calibration of intrinsic and extrinsic camera parameters. The matrix transformation is between the frames in the camera coordinate system and in the image plane. The vision sensor data are in fact perspective projection constraints on object vertices. The data relationship between image vertices and object vertices is one to one mapping. At most one image vertex corresponds to an object vertex. Assume the camera is mounted on the robot end-effector, the kinematic model of the robot is written as:

$$f_c = f(q) \tag{8}$$

where f_c is the camera position vector and it is a function of joint displacement q. Assume f_o (6×1) is the object position vector, the object image representation in the camera coordinate system can be described as:

$$r = T_w^C (f_o - f_c) \tag{9}$$

where T_w^C is a coordinate transformation matrix that represents the orientation of the camera coordinates with respect to the world frame. The matrix T_w^C can be expressed as the product of transformation matrices T_{obj}, T_{robot} and T_{cam}. Where, T_{obj} is the transformation matrix from the real world object to the base coordinate frame of the robot. T_{robot} is a rotation matrix from the base robot coordinate frame to the end-effector of the n-link robot, which combines several transformation matrices of the linked arms or joints. T_{cam} is the transformation matrix from robot end-effector to the camera coordinate system. We have:

$$T_w^C = T_{obj} T_{robot} T_{cam} \tag{10}$$

F. Ultrasound Feature Transformation Model

Unlike X-ray, light and radio wave, ultrasound has no electromagnetic radiation and it acts as a mechanical disturbance where oscillations travel through soft tissues and fluids. It can be used in image processing. A higher ultrasonic frequency gives rise to a better resolution. Ultrasound sensor is a reflective sensor that responds to changes in the amount of emitted energy returned to a detector after interaction with the target object. The echo returning time is proportional to transmission distances. The ultrasound transmitter emits a burst of ultrasonic energy and the ultrasound receiver captures the incoming signals to determine the object position. The real time 3D ultrasound feature can be accurately reconstructed by the ultrasound image system and the graphic user interface. Assume the coordinate representation of a feature point in the ultrasound probe frame is a vector $V = [x_i, y_i, z_i]^T$. The relationship of different coordination systems is:

$$V = T (P_f - P_b) \tag{11}$$

where the elements of vector P_f (2×1) are the coordinates of one feature point in the base coordinate frame, the elements of vector P_b (2×1) are end-effector coordinates in the base coordinate frame, matrix T (3×2) represents coordinate transformation from the base frame to the end-effector frame, similar to T_{robot} in the camera model.

G. Raman & Infrared Spectra Approximation

Raman spectroscopy is used for species detection by sending monochromatic light on the sample to analyze the scattered light. When the light with an electric field intensity $E = E_0\cos(\omega t)$ is incident on molecules of the sample surface, the scattered light from the surface will emit at three frequencies: ω, ω-ω_0 and ω+ω_0, where ω_0 is the natural frequency of the molecule vibrating. The main part of the scattered light contains the wavelength with the incident frequency. The interaction of the incident light with optical photons is called Raman Scattering and it results in the very low intensity light at frequency ω-ω_0 and ω+ω_0, named Stokes radiation and anti-Stokes radiation, respectively. In scattering process, incidental photons are destroyed and the energy is used to create scattered photons and to either create or destroy vibrations. By knowing the frequency of the incident monochromatic light and measuring the frequency of Raman scattered light, the natural frequency of sampling molecule can be determined so as to recognize the body tissue conditions. The spectrum from the sample consists of an intrinsic Raman spectrum (R) and a background spectrum (B). The extract Raman spectrum is obtained by difference between the background spectrum and the measured spectrum (S).

Given that each spectrum has n_2 measured elements and the spectrum can be approximated as a polynomial with its order equivalent to (n_1-1). Suppose S = R+B = AC, where A ($n_1\times n_2$) is a matrix obtained from the measured spectrums and C ($n_1\times1$) is its coefficient vector. The fitting polynomial is given by least squares estimation:

$$\check{S} = A(A^TA)^{-1}A^TS = A(A^TA)^{-1}A^T(R+B) \tag{12}$$

The extracted Raman spectrum ($\check{R}$) with two frequencies of ω-ω_0 and ω+ω_0 can be calculated as:

$$\check{R} = S - \check{S} = (R+B) - A(A^TA)^{-1}A^T(R+B)$$
$$\approx R - A(A^TA)^{-1}A^TR \tag{13}$$

From equation (13), $\check{R}$ is a function of Raman spectrum exclusively, which is independent of the environment. The natural frequency of sampling molecule can then be distinguished. The assumption is $B \approx A(A^TA)^{-1}A^TB$ in a slow varying process, so that the estimated background spectrum can represent the actual background spectrum.

Infrared spectroscopy and Raman spectroscopy allow the measurement of frequencies with the same magnitude order as infrared light. Both of them adsorb the photons during the energy transition. For infrared spectroscopy, there are dipole moment changes instead of polarization changes of Raman spectroscopy. The measured spectrum by infrared spectroscopy is also comprised of both the intrinsic infrared spectrum and the background spectrum from the environment. Similarly, the extracted infrared spectrum can be obtained by the least squares estimation approach. The wave numbers are then determined and can be used to recognize the body tissue conditions.

IV. MULTISENSOR INTERGRATION

The integration of various sensors in the robotic system and the complex environment make it difficult to select model structure and parameters. Different sensors might capture diverse types of data from the same environment. So multiple sensor models are necessary. Any observed data features can be correspondent to the environment feature through some constraint relations. It is important to augment the robotic functions with different sensing devices in order to improve the robot control efficiency. Individual device generally can only obtain insufficient information for feature extraction. For example, the delay and slow sample rate of a CCD camera might be possible to make the feedback system oscillatory or even unstable. It is necessary to ensure the stability and the accuracy. There is still no robotic framework that can cover all the aspects by multisensor integration within a feedback control loop. As the major part of multisensor integration, multisensor data fusion covers two sensor fusion approaches. The explicit approach is to build an internal representation or environment model from the sensing data. The implicit approach transforms sensing directly to action without an explicit representation.

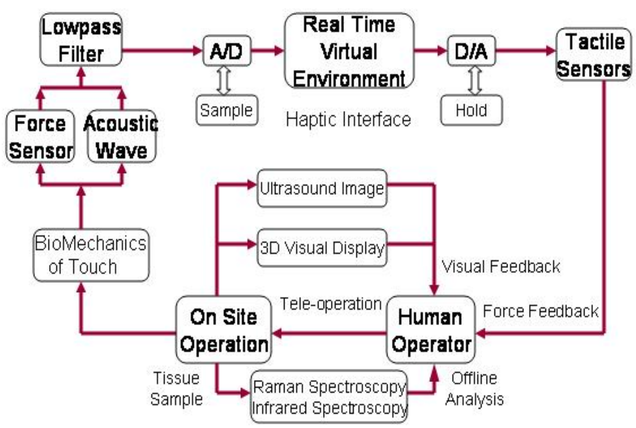

Figure 2 Flowchart of Robot Integration System

Visual servoing systems incorporate vision sensors in the feedback loop. The benefit of feedback control loop is obtained by attaching a camera close to the end-effector. The robotic object recognition can be either position-based or feature-based. The position-based approach estimates the object position and orientation in real time but it is quite sensitive to image distortion and noises. Feature-based approach processes the object features directly to derive a visual output without the position and orientation computation, which is robust against the calibration errors and noises. This approach has difficulties when object features become occluded or object motion alters the feature beyond recognition. The contour extraction can provide useful information to the visual servoing system. The sensing data errors may be described as uncertainty models with certain probability distribution.

Robotic touch and vision fusion is for the combination of the image data with the touch force data to improve the capability of accurate object recognition by sensation of interacting with a real physical environment. The fusion of vision with ultrasound can be explored to facilitate and enhance the object recognition. Tactile and vision fusion is used to combine multiple tactile contact sensing data with visual data features to determine the position and orientation for guiding the robot manipulation. The tactile sensors extract touch position and approximate the surface normal in a kinematic reference frame of the robot end-effector. The analysis of Raman and infrared spectrum is also helpful to determine the conditions of the investigated objects.

Considering the force and visual information, the robot manipulator dynamics is expressed as:

$$M(q)\ddot{q} + C(q, \dot{q})\dot{q} + G(q) + J^T(q)F = \tau \qquad (14)$$

where, $J_e(q)$ is the Jacobian matrix relating joint space velocity to task space velocity. F can be a touch force or tactile force (F_T) and it can also be a piezoelectric force of acoustic wave sensors (F_A). Considering the motion of end-effector and the equation (5), the relation between the joint velocity and the manipulator velocity is:

$$\dot{Z} = J_o(p)\,\dot{p} = J_e(q)\,\dot{q} \qquad (15)$$

where Z is the generalized coordinates of the object position and it is also the output of the robot dynamic model. Assume the manipulators work in a nonsingular region. Then we have:

$$\dot{q} = J_e^{-1}(q)\, J_o(p)\,\dot{p} \qquad (16)$$

With the effect of ultrasound visualization, the object image vector can be described as:

$$R_{obj} = T_{overall}\,(P_o - P_c) \qquad (17)$$

where P_c is the sensor position vector and P_o is the object position vector. Both the camera and ultrasound image data elements are taken into account within the vectors of P_c and P_o. $T_{overall}$ is the transformation that represents the orientation of the visual coordinates with respect to the world frame. R_{obj} is the object image vector in terms of both the camera sensing and the ultrasound sensing.

V. MODEL REFERENCE ADAPTIVE CONTROL LAW

The force and position control law:

$$\tau = M(q)J^{-1}(q)[u_1 - \dot{J}(q)\dot{q}] + C(q, \dot{q})\dot{q} + G(q) + J^T(q)u_2 \qquad (18)$$

where u_1 is the position and orientation control command and u_2 is the force control command. The torque τ has to be within certain constraint ($\tau_{min} \le \tau \le \tau_{max}$) dependent on applications. Assume Z_m, V_m and A_m as the desired position, velocity and acceleration vectors of the robot manipulator model. Also assume F_m as the desired force vector that handles the object.

A simple PID control command can be applied to actual object position (Z) control and a PI control command can be applied to the actual force (F) control.

$$u_1 = \ddot{Z} + k_p(\dot{Z}_m - \dot{Z}) + k_i(Z_m - Z) \quad (19)$$

$$u_2 = F_m + k_{fp}(F_m - F) + k_{fi}\int(F_m - F)dt \quad (20)$$

where k_p, k_i, k_{fp}, k_{fi} are the correspondent coefficients.

On a basis of the system reference model from the robot design, model reference adaptive control can be used to solve the feedback control problem.

VI. Conclusion

The focus of this work is to analyze the feasibility of multisensor integration application on the improvement of the robot control. The simplified models for the visual systems and haptic systems have been presented and the integrated model for force control and position control is given. Some additional techniques for measurement and recognition on sensor integration are also investigated. A feedback control law is proposed for the robot system identification and adaptation. The idea is to present some simple models for a relatively complete description of robotic smart sensor integration research. The proposed control scheme consists of both the feedforward part and the feedback part.

VII. Future Work

This work is the preliminary research on integration of the haptic and visual feedback control application on the robotic smart sensor integration. The hapic interface and visual interface prototypes are completed in the related research. The important issues for the next step are the high resolution sensor fabricating, the redundant multiple sensor information processing and the real time feedback control application.

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