Sensor Fusion and Object Localization

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Abstract

In this paper, we discuss the issue of locating objects through multiple sensory information. Sensor measurements are subject to limitations of sensor precision and accuracy. Although errors in position estimates are affected only by the errors of sensor measurements, errors in orientation estimates are also dependent on the dimensions over which the measurement has been made. The concept of *good measurement* is used in selecting and weighting partial estimates of the position and orientaion. The problem of finding the best estimate of the position and orientation is formulated as a linear system of these multiple estimates. The best estimate is then obtained by solving this system in a weighted least square sense. This method has been implemented for a manipulator end-effector instrumented with centroid and matrix tactile sensors.

1. Introduction

An important characteristic of robots aimed at accomplishing advanced tasks is their ability to ascertain the state of their workspaces. The uncertainties in the position and orientation of an object with respect to a manipulator are primarily due [Brooks 1983] to mechanical errors in the position and orientation of the object in the workspace, dimensional tolerance in the object, and errors in commanding the manipulator to a desired position. Such uncertainties cannot be recovered prior to actual operations. A robust program will generate actions that depend on real-time sensory information. Expected errors in such sensory information will also allow an assembly planning system to determine if an operation will eventually succeed.

The problem of locating an object using sensory information has so far received attention only as a part of the problem of object recognition. Grimson and Lozano-Perez [Grimson and Lozano-Perez 1984] proposed a solution using simple geometric relations based on pairs of observations. Faugeras and Hebert presented [Faugeras and Hebert 1983] a least square estimation method for the position and orientation obtained from redundant measurements. On the other hand, insufficient measurements lead to an indeterminate problem. In the context of task level specification, a symbolic solution for the position and orientation based on spatial relationships has been proposed in [Popplestone, Ambler, and Bellos 1980].

In this paper, we present a method for estimating the position and orientation of objects using multiple sensory information. Sensor measurements are subject to limitations of sensor reliability and precision. These limitations impose an order of relative importance on the measurements. We define *good measurements* and present a weighting scheme of the measurements. Frequently, there is redundancy in measurements that leads to an overdetermined system. We solve the weighted system of measurements for the best estimate of the position and orientation, and determine the boundaries of the largest errors. Finally, we describe the application of this method to the location of an object in a two fingered two-degree-of-freedom end-effector using two pressure conductive rubber centroid sensors and a matrix tactile sensor.

2. Problem Definition

Measurements

Device measurements are characterised by their precision and reliability. Precision is the built in ability of a sensor to resolve measurements and reliability is the measure of systematic errors. When measurements have to be processed in order to produce useful information, additional error due to this extraction process must be considered. Finally, we characterize sensor measurements in the form $m \pm \Delta m$.

Position and Orientation

To each sensor measurement of an identifiable feature of

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the object, there is a corresponding measure of that feature in the object's model. The objects have six degrees of freedom with respect to the sensors. Thus,

$$^{s}\mathbf{p}_k = \mathbf{R}\,^{o}\mathbf{p}_k + \mathbf{h}; \quad (1)$$

represents the transformation of the k^{th} point $^{o}\mathbf{p}_k$ described in the object frame of reference to its description $^{s}\mathbf{p}_k$ in the sensor frame. $\mathbf{R}$ is the 3×3 rotation transformation matrix, and $\mathbf{h}$ is the position vector of the origin of the object frame in the sensor frame. We will assume that all sensor measurements are described in a global measurement frame of reference.

Given sensor measurements $^{s}\mathbf{p}_k$'s and corresponding values of $^{o}\mathbf{p}_k$'s from the object model, there are three position and three orientation parameters to solve for. The orientation components and the position components are solved independently. The orientation is evaluated from

$$^{s}\mathbf{v}_i = \mathbf{R}\,^{o}\mathbf{v}_i; \quad (2)$$

where $^{s}\mathbf{v}_i$ and $^{o}\mathbf{v}_i$ are either vectors obtained from one sensor measurement, or from points as,

$$^{s}\mathbf{v}_i = (^{s}\mathbf{p}_k - ^{s}\mathbf{p}_l);$$
$$^{o}\mathbf{v}_i = (^{o}\mathbf{p}_k - ^{o}\mathbf{p}_l);$$

The position parameters are evaluated from a scalar equation on distance. For any distance measurement $^{s}d_i$ in the sensor along a direction $^{s}\mathbf{n}_i$ there is a distance $^{o}d_i$ in the model computed along $^{s}\mathbf{n}_i$. These two measurement are related by [Faugeras and Hebert 1983]

$$^{s}\mathbf{n}_i^{T}\mathbf{h} = {^{s}d_i} - {^{o}d_i}. \quad (3)$$

Measurements of at least two independent vectors is required to uniquely determine the orientation parameters and at least one vertex or three non-parallel plane measurements to solve for position parameters. However, there are often more measurements than the least required for unique solution. In such cases measurements can be tested against their contribution to the error in the solution.

Good Measurements

The notion of *good measurements* is associated with the error a measurement contributes to the solution. In this section, we discuss this notion for the evaluation of orientation and position parameters.

Orientation Estimate

The partial estimates of the orientation of an object are evaluated from object features *e.g.*vertices, edges, faces and normals. A partial estimate of orientation is strongly dependent on the way sensor measurements are combined. Estimates that are obtained from two vertices, for example, improve when the vertices are far apart. Estimates also improve with the lengths of edges or the surface of faces. A good selection of features as well as the combination of sensors will contribute, therefore, to significant improvement in the final estimate of the orientation. The selection can be based on the evaluation of the associated errors in orientation. An orientation error vector can then be used to characterize each partial estimate of the orientation. Let us consider, for example, the partial estimate of orientation obtained from two vertices measured by the sensors k and l. The orientation error about the z-axis, in the common sensor frame of reference, can be computed from the errors in xy plane (see fig. 1)

$$\begin{aligned}\delta\phi_{z_i} &= \phi_2 - \phi_1; \\ &\simeq \tan(\phi_2 - \phi_1); \\ &= \frac{v_{y_i}(v_{x_i} + \Delta v_{x_i}) - v_{x_i}(v_{y_i} - \Delta v_{y_i})}{v_{x_i}(v_{x_i} + \Delta v_{x_i}) + v_{y_i}(v_{y_i} - \Delta v_{y_i})};\end{aligned} \quad (4)$$

where

$$\Delta v_{x_i} = \Delta m_{x_k} + \Delta m_{x_l};$$
$$\Delta v_{y_i} = \Delta m_{y_k} + \Delta m_{y_l}.$$

The orientation errors $\delta\phi_{x_i}$ and $\delta\phi_{y_i}$ can be similarly obtained. An estimate of the orientation can then be characterized by the magnitude $\delta\Phi_i^{T}\delta\Phi_i$ of the orientation error vector $\delta\Phi_i$. A selection procedure based on these magnitudes will determine the most significant set of partial estimates of the orientation. The $\delta\Phi_i^{T}\delta\Phi_i$ will also provide weighting for the selected set of partial estimate that will be used to determine the final estimate of the orientation.

Position Estimate

The solution of position parameters from equation (3) is based on estimate of vertices or plane distances from the origin. Each such estimate can be simply characterized by the error in the distance measurement and $\{\delta d^2\}$ will be used to weight each distance measurement.

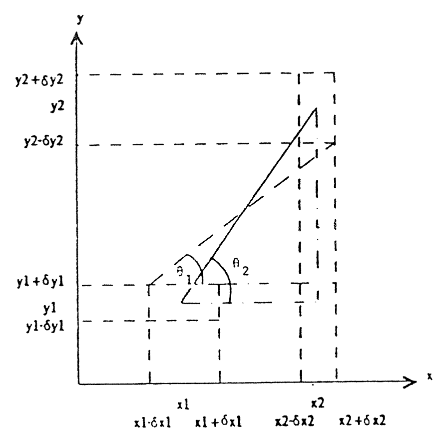

Fig. 1. Angular Uncertainty.

Orientation Representations

The elements of $\mathbf{R}$ in any of the three well known representations namely Euler angle representation, roll, pitch, yaw representation and axis-angle representation, must be solved with the condition that $\mathbf{R}^T\ \mathbf{R} = \mathbf{I}$; where $\mathbf{I}$ is 3×3 identity matrix. It requires solution of nine parameters of $\mathbf{R}$ with six quadratic conditions of orthonormality on $\mathbf{R}$ in addition to at least three linearly independent measurement constraints.

Using quaternions, the problem of orientation estimate reduces to finding the solution of a linear system with the normality condition on Euler parameters. A brief review of quaternions and orientations is presented in Appendix A.

Orientation Parameters

We first reduce the solution of orientation parameters to solution of a linear system. Then, we solve the system using a weighted left inverse matrix. If $(\mathbf{q} = (u_0, \mathbf{u}))$ represents the quaternion corresponding to the transformation $\mathbf{R}$, then rewriting the transformation (A7) in the appendix

$$ {}^s\mathbf{v}_i\mathbf{q} = \mathbf{q}\,{}^o\mathbf{v}_i. \tag{5}$$

Equating the scalar and vector parts of this equation yields,

$$({}^s\mathbf{v}_i + {}^o\mathbf{v}_i) \times \mathbf{u} = u_0({}^o\mathbf{v}_i - {}^s\mathbf{v}_i); \tag{6}$$

$$\mathbf{u} \cdot ({}^s\mathbf{v}_i - {}^o\mathbf{v}_i) = 0. \tag{7}$$

The orientation parameters are completely determined by equation (6) when expressed in a frame where $({}^s\mathbf{v}_i + {}^o\mathbf{v}_i)$ is a non-zero vector. Such a frame can always be selected by simple examination of ${}^s\mathbf{v}_i$ and ${}^o\mathbf{v}_i$. The system (5) can then be solved by (6) which can be expressed as a linear system

$$\mathbf{A}_i\mathbf{u} = u_0\mathbf{b}_i; \tag{8}$$

where $\mathbf{A}_i$ is the cross product operator of $({}^s\mathbf{v}_i + {}^o\mathbf{v}_i)$, the sum vector, and $\mathbf{b}_i$ is the difference vector $({}^o\mathbf{v}_i - {}^s\mathbf{v}_i)$. The system of equations for multiple estimates is

$$\mathbf{A}\mathbf{u} = u_0\mathbf{b}; \tag{9}$$

where

$$\mathbf{A} = [\mathbf{A}_1^T, \mathbf{A}_2^T, ..., \mathbf{A}_n^T]^T;$$
$$\mathbf{b} = [\mathbf{b}_1^T, \mathbf{b}_2^T, ..., \mathbf{b}_n^T]^T.$$

The weighting matrix for each estimate is defined as

$$\mathbf{W}_{r_i} = w_{r_i}^2\mathbf{I}; \tag{10}$$

where

$$w_{r_i} = 1/(1 + \delta\Phi_i{}^T\delta\Phi_i)^2;$$

and $\mathbf{I}$ designates the 3×3 identity matrix. The weighted system of equations is

$$\mathbf{W_r}\mathbf{A}\mathbf{u} = u_0\mathbf{W_r}\mathbf{B}; \tag{11}$$

where

$$\mathbf{W_r} = diag(\mathbf{W}r_i).$$

Using the normality condition of Euler parameters, the solution of the system is given by

$$\begin{aligned} u_0 &= 1/\sqrt{1 + \mathbf{g}^T\mathbf{g}}; \\ \mathbf{u} &= u_0\mathbf{g} \end{aligned} \tag{12}$$

where

$$\mathbf{g} = \mathbf{G}\mathbf{b}; \tag{13}$$

and G represents the weighted left inverse matrix

$$\mathbf{G} = (\mathbf{A}^T\mathbf{W_r}\mathbf{A})^{-1}\mathbf{A}^T\mathbf{W_r}. \tag{14}$$

The rotation matrix $\mathbf{R}$ corresponding to the solution $\mathbf{q} = (u_0, \mathbf{u})$ of equations (12) is given [Khatib 1980] by,

$$\mathbf{R} =$$
$$\begin{bmatrix} 2(u_0{}^2 + u_1{}^2) - 1 & 2(u_1u_2 - u_0u_3) & 2(u_1u_3 + u_0u_2) \\ 2(u_1u_2 + u_0u_3) & 2(u_0{}^2 + u_2{}^2) - 1 & 2(u_2u_3 - u_0u_1) \\ 2(u_1u_3 - u_0u_2) & 2(u_2u_3 + u_0u_1) & 2(u_0{}^2 + u_3{}^2) - 1 \end{bmatrix} \tag{15}$$

Orientation Error Vector

We have determined the estimate of the orientation of the object in a weighted least square sense. The estimate $\mathbf{q}$ lies within $\mathbf{q} \pm \delta\mathbf{q}$. The $\delta\mathbf{q}$ can be determined by considering the contribution of $\delta\mathbf{q}_i$'s from each measurement in the same weighted least square sense as

$$\delta\mathbf{q} = (\Sigma_i w_{r_i}\delta\mathbf{q}_i)/(\Sigma_i w_{r_i}^2). \tag{16}$$

The uncertainty of each measurement has been characterized by the elementary rotation vector $\delta\Phi_i$ (see equation 4). To an elementary rotation vector $\delta\Phi_i$ corresponds an elementary variation $\delta\mathbf{q}$ given by [Khatib 1980]:

$$\delta\mathbf{q}_i = \frac{1}{2}\check{\mathbf{q}}\delta\mathbf{\Phi}_i; \tag{17}$$

where

$$\check{\mathbf{q}} = \begin{bmatrix} -u_1 & -u_2 & -u_3 \\ u_0 & u_3 & -u_2 \\ -u_3 & u_0 & u_1 \\ u_3 & -u_1 & u_0 \end{bmatrix}. \tag{18}$$

The equation (16) becomes

$$\delta\mathbf{q} = \frac{1}{2}\check{\mathbf{q}}(\Sigma_i w_{r_i}\delta\Phi_i)/(\Sigma_i w_{r_i}^2). \tag{19}$$

Position Parameters

The position parameters are linear functions of distance measurements as defined in equation (3). For multiple measurements, equation (3) becomes,

$$\mathbf{C}\ \mathbf{h} = \mathbf{d}; \qquad (20)$$

where

$$\mathbf{C} = [{}^s\mathbf{n}_1, {}^s\mathbf{n}_2, ..., {}^s\mathbf{n}_2]^T;$$
$$\mathbf{d} = [d_1, d_2, ..., d_n]^T.$$

The weighted system of equations with weights defined for each distance measurement as $w_{p_i} = \delta d_i^2$ becomes

$$\mathbf{w}_p\ \mathbf{C}\ \mathbf{h} = \mathbf{w}_p \mathbf{d}. \qquad (21)$$

The solution is

$$\mathbf{h} = \Sigma \mathbf{d}; \qquad (22)$$

where

$$\Sigma = (\mathbf{C}^T \mathbf{w}_p^T \mathbf{w}_p \mathbf{C})^{-1} (\mathbf{C}\mathbf{w}_p)^T \mathbf{w}_p.$$

The uncertainty in the estimate of the position $\mathbf{h}$ due to uncertainty in measurement of ${}^s d_i$ is given by

$$\delta\mathbf{h} = \Sigma \delta\mathbf{d}; \qquad (17)$$

where

$$\delta\mathbf{d} = [\delta d_1, \delta d_2, ..., \delta d_n]^T;$$

3. Sensor Description

A matrix tactile sensor and two centroid sensors has been selected for instrumentation of the end-effector. We include a review of the sensor's working principles and characteristics. A more detailed description can be found in [Ishikawa and Shimojo 1982] and [Shimojo and Ishikawa 1985].

Matrix Tactile Sensor

The matrix tactile sensor has 8×8 elements each of 5mm square dimension. It outputs pressure distribution information on a grey scale. In addition, it has one output each from a proximity sensor and a thermal sensor.

Working Principle and characteristics

Pressure measurement is based on change in resistivity of a thin pressure conductive rubber mounted on the surface. The change in resistivity is measured through a gold plated electrode pattern as shown in figure 2 etched on the surface of the circuit board. The change in resistivity as a function of pressure is shown in figure 3. The sensor has custom designed hybrid IC's mounted at the back for multiplexing the 66 analog outputs of the array over a single channel in frequency modulated form.

Centroid Sensor

The centroid sensor outputs the center of pressure of a two dimensional pressure distribution and the total force applied. As the sensor is made of thin material, it is pliable and has sheet like form. The center of pressure and total force output are direct and do not require any computational effort.

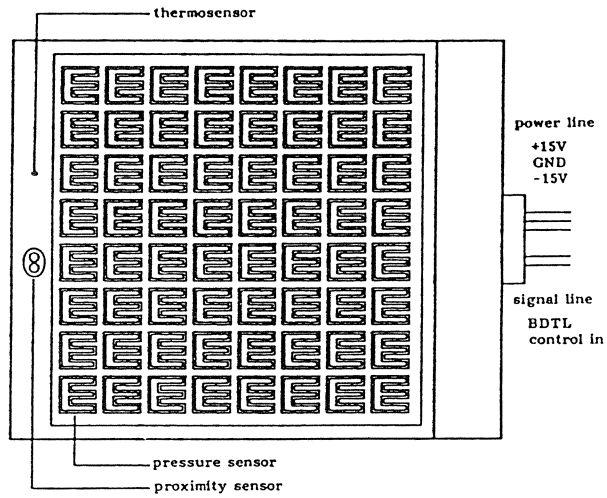

Fig. 2. Structure of the Tactile Sensor.

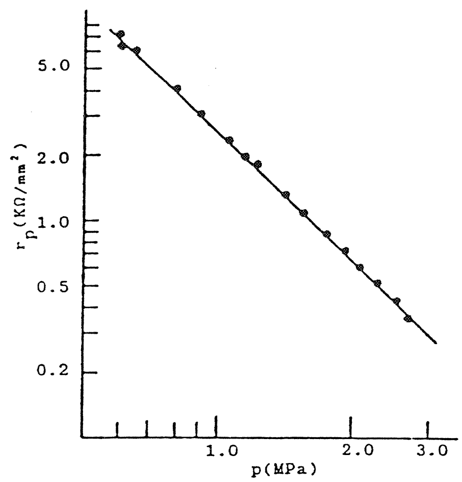

Fig. 3. Pressure Response of Conductive Rubber.

Working Principle and Characteristics

As shown in figure 4, the sensor has a three-layered structure.The layers A and B are made of electrically conductive material coated film. The layer S is made of pressure conductive rubber. The resistance $r_p(x, y)$ of the rubber along the thickness varies according to the pressure distribution. The boundary of the sensor divided into S_1, S_2, S_3, S_4 is surrounded by electrodes that contact with layer A or b and connect to constant voltage sources V_0 via resistor R.

The drop in resistance $r_p(x,y)$ of the rubber due to a pressure distribution causes a current distribution $i(x,y)$ proportional to the resistance drop. The current density induces a voltage distribution $v(x,y)$ on the surface of layers A and B. The current density and the induced voltage are related through Poisson's equation

$$\nabla^2 v = ri; \qquad (\nabla^2 = \frac{\delta^2}{\delta x^2} + \frac{\delta^2}{\delta y^2}); \tag{23}$$

where r is surface resistance in the layer. The first order moments of the current density distribution in the cartesian coordinates and the total current are given by

$$I_x = \int\int_D xi(x,y)dxdy;$$
$$I_y = \int\int_D yi(x,y)dxdy;$$
$$I = \int\int_D i(x,y)dxdy;$$

With rectangular boundary conditions on equation (23), the following expressions are obtained:

$$I_x = a(\frac{1}{R} + \frac{2}{r})([v_A]_{S_1} - [v_A]_{S_3}); \tag{24}$$
$$I_y = a(\frac{1}{R} + \frac{2}{r})([v_B]_{S_2} - [v_B]_{S_4}); \tag{25}$$
$$I = \frac{2V_0 - [v_A]_{S_1} - [v_A]_{S_3}}{R}. \tag{26}$$

The total force is derived from equation (26) and with known relation between current distribution and the pressure distribution, the equations (24),(25) and (26) give the center of pressure.

4. Experimental Results

In this section, we present an application of this method in locating a grasped object. The mechanical uncertainty in the position and orientation of objects in the workspace, their dimensional tolerance and the error in commanding the gripper to a specified location makes the position of the object uncertain with respect to the gripper. Since such uncertainties can not be determined ahead of time, a robust assembly program will use the sensory information at real-time to update the position and orientation of the object.

We mounted on a two-degree-of-freedom parallel jaw gripper the tactile sensor on one finger, a centroid sensor on the other finger and a centroid sensor on the palm (see fig. 4). An example of a grasped object is shown in fig. 5. A partial estimate of the object's orientation was obtained from 8×8 tactile sensor (see fig 6). The two centroid sensors provided another partial estimate of the orientation. The error on the final estimate obtained from the weighted least square solution was ±0.2 degrees.

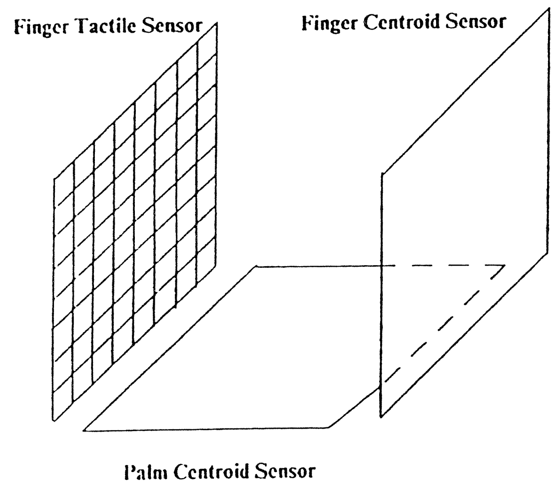

Fig. 4. Gripper with Tactile and Centroid Sensors.

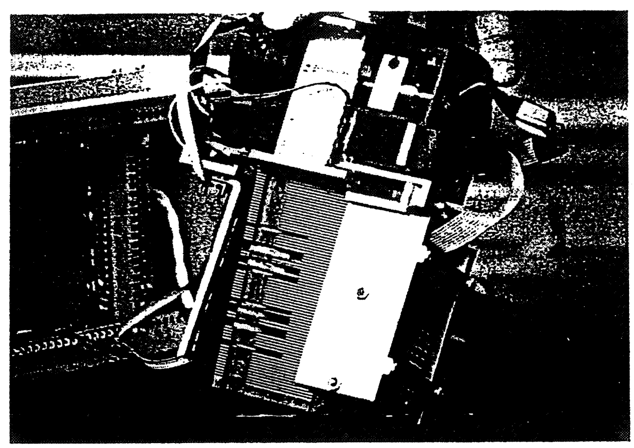

Fig. 5. The Instrumented End-Effector.

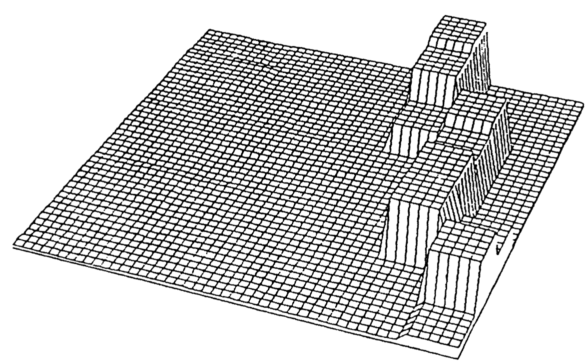

Fig. 6. Matrix Tactile Sensor Output.

4. Conclusion

In this paper, a framework for the integration of multiple sensors to determine the position and orientation of an object has been proposed. We defined *good measurements* in the sense of determining best estimate of these parameters. The best estimate is obtained as the solution of weighted linear system of equations. This leads to a computationally efficient algorithm for real-time applications. An end-effector has been instrumented with centroid and matrix tactile sensors, and an example of object location has been presented.

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Appendix: Quaternions

Let (u_0, u_1, u_2, u_3) be the components of the quaternion

$$\mathbf{q} = u_0 + \mathbf{i}u_1 + \mathbf{j}u_2 + \mathbf{k}u_3. \tag{A1}$$

A convenient representation of quaternions uses a scalar u_0 and a vector $\mathbf{u} = \mathbf{i}u_1 + \mathbf{j}u_2 + \mathbf{k}u_3$,

$$\mathbf{q} = (u_0, \mathbf{u}). \tag{A2}$$

Operations of quaternions addition and product are defined by,

$$\begin{aligned} \mathbf{q} + \mathbf{q}' &= (u_0 + u_0') + \mathbf{i}(u_1 + u_1') \\ &\quad + \mathbf{j}(u_2 + u_2') + \mathbf{k}(u_3 + u_3';) \\ \mathbf{q}\mathbf{q}' &= (u_0 u_0' - \mathbf{u}\cdot\mathbf{u}', \mathbf{u}\times\mathbf{u}' + u_0\mathbf{u}' + u_0'\mathbf{u}). \end{aligned} \tag{A3}$$

The conjugate or inverse of a quaternion is defined as

$$\mathbf{q}^* = (u_0, -\mathbf{u}). \tag{A4}$$

Quaternions represent rigid body rotation if the components of quaternion $\mathbf{q}$ are the set of four Euler symmetric parameters corrosponding to a rigid body rotation defined by transformation $\mathbf{R}$. The set of Euler parameters for rotation about unit axis $\mathbf{r}$ of an angle θ or about unit axis $-\mathbf{r}$ of an angle $-\theta$ are:

$$\begin{aligned} u_0 &= cos(\theta/2); \\ \mathbf{u} &= sin(\theta/2)\mathbf{r}. \end{aligned} \tag{A5}$$

with

$$u_0^2 + u_1^2 + u_2^2 + u_3^2 = 1 \tag{A6}$$

The transformation of ${}^o\mathbf{v}$ to ${}^s\mathbf{v}$ as in equation (2) is effected in quaternion algebra by the operation

$${}^s\mathbf{v}_i = \mathbf{q}\,{}^o\mathbf{v}_i\mathbf{q}^*; \tag{A7}$$

where ${}^o\mathbf{v}_i$ and ${}^s\mathbf{v}_i$ are equivalent to the quaternions $(0, {}^o\mathbf{v}_i)$ and $(0, {}^s\mathbf{v}_i)$.