A Fastening Tool Tracking System Using an IMU and a Position Sensor With Kalman Filters and a Fuzzy Expert System

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***Abstract*—This paper utilizes an intelligent system which incorporates Kalman filters (KFs) and a fuzzy expert system to track the tip of a fastening tool and to identify the fastened bolt. This system employs one inertial measurement unit and one position sensor to determine the orientation and the center of mass location of the tool. KFs are used to estimate the orientation of the tool and the center of mass location of the tool. Although a KF is used for the orientation estimation, orientation error increases over time due to the integration of angular velocity error. Therefore, a methodology to correct the orientation error is required when the system is used for an extended period of time. This paper proposes a method to correct the tilt angle and orientation errors using a fuzzy expert system. When a tool fastens a bolt, the system identifies the fastened bolt using a fuzzy expert system. Through this bolt identification step, the 3-D orientation error of the tool is corrected by using the location and orientation of the fastened bolt and the position sensor outputs. Using the orientation correction method will, in turn, result in improved reliability in determining the tool tip location. The fastening tool tracking system was experimentally tested in a lab environment, and the results indicate that such a system can successfully identify the fastened bolts.**

***Index Terms*—Accelerometer, expert system, fuzzy logic, gyroscope (gyro), inertial measurement unit (IMU), Kalman filter (KF).**

I. Introduction

RECENTLY, quality control has been a primary focus in the automotive industry. However, many automotive parts are still produced without any quality control process. For instance, all bolts of automotive parts should be fastened in the correct places, but fastening processes usually do not have any quality control system. In this scenario, operators are responsible for the final quality of the parts. It is not uncommon in such environment that operators make mistakes by missing bolts or fastening a bolt in the wrong place. To eliminate these mistakes and correctly identify the fastened bolts, a quality control system that tracks the location of the tool tip, where bolts are placed during fastening, is required.

This paper presents a fastening tool tracking system that identifies which bolt a right angle fastening tool, which is the most widely used tool in automotive industries, has fastened using one inertial measurement unit (IMU) and one position sensor. An IMU consists of three accelerometers and three gyroscopes (gyros) that measure three linear acceleration components and three angular velocity components of the body frame. Assuming that the local gravity vector is constant, the position and the orientation of an object can be accurately calculated by numerically integrating the linear acceleration and angular velocity measured by an ideal IMU which has continuous and perfectly accurate measurements. In real world, however, the position error of an IMU increases over time dramatically due to single integration of angular velocity measurements and double integration of acceleration measurements that include undesirable properties such as nonlinearity and noise. This deemed an IMU suitable for the use as an orientation sensor [1], [2]. However, the orientation calculation also drifts over time due to the integration of gyro error; hence, an orientation correction system is required. Tilt angle correction methods have been proposed in the literatures, which use accelerometers as an inclinometer [3]–[6]. A Kalman filter (KF) was used to estimate the tilt angles in [3] and [4], and a fuzzy expert system is employed to correct the tilt angles when a vehicle is stationary [5]. Rehbinder and Hu [6] applied a logic system to detect acceleration-free motion and used a hybrid KF to estimate the roll and pitch angle with three accelerometers and three gyros.

In order to find the position and the orientation of an object, hybrid systems that aggregate an IMU with a position sensor are widely used [7]–[11]. Such systems usually utilize a KF or an extended KF to estimate the position [8]–[11]. Hybrid sensor configurations that use an ultrasonic position sensor and an IMU to estimate three position and three orientation components are presented in [8] and [9]. However, the performance issues related to reflections, occlusions [7], and maximum emitting angle limit their use in automotive industries. Another hybrid option is a camera vision system integrated with an IMU [10]. This method uses a camera as a position sensor. When occlusion is encountered, an IMU is used to find the position. In this case, the position error dramatically increases in a short period of time. An attempt to determine the position of a tool by using an optical position sensor integrated with an IMU is reported in [11]. This system has good long term accuracy. However, optical sensors are very expensive, and when an occlusion is encountered, the position error increases because only an IMU is used to estimate position.

Manuscript received May 2, 2008; revised August 6, 2008. First published November 25, 2008; current version published April 29, 2009.

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Digital Object Identifier 10.1109/TIE.2008.2010166

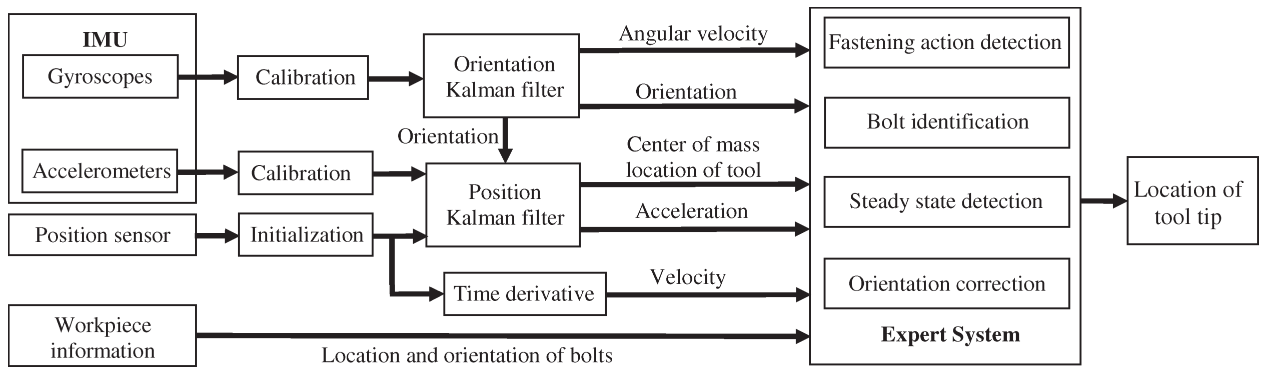

Fig. 1. Overview of the proposed fastening tool tracking system.

A string-encoder position sensor can find 3-D position with high accuracy and provides noise-free outputs. A string-encoder position sensor is a good option for the fastening tool tracking system because those tools are often hung on a balancer in automotive industries. Since the position sensor should act as a balancer and support a fastening tool, the end of the wire is connected to the center of mass of the tool. Thus, the position sensor outputs the location of the center of mass of the tool instead of the tool tip. To determine the position of the tool tip with a string-encoder position sensor, an IMU is used as an orientation sensor.

Expert systems, which are a branch of artificial intelligence, are very powerful decision-making tools and are used in various industries such as textile companies, steel companies, and printed circuit board manufacturing for quality control [12]–[14]. Expert systems consist of a knowledge base, a reasoning mechanism, and a user interface [15]. The knowledge base in a classical expert system is constructed with facts and rules that are expressed in Boolean logic. Rules are often expressed in a form of "IF A, THEN C," where A is a set of antecedent conditions and C is a set of consequences. In classical logic, the consequence C is true when the antecedent A is perfectly satisfied. A fuzzy expert system that utilizes fuzzy sets [16] and fuzzy logic [17], [18] allows quantifying how true the consequence is based on how closely the antecedent is satisfied by using membership degree ranging from zero to one, where zero represents false and one represents true. Due to the capacity of finding outputs when inputs have uncertainties, fuzzy expert systems are widely used in various applications including inertial navigation systems [5], [19], [20]. Some research works combined fuzzy logic and KF to estimate the position of an object more accurately [21], [22].

The proposed system uses a string-encoder position sensor to locate the center of mass of the tool and a microelectromechanical system (MEMS) IMU to find the orientation of the tool. This paper proposes KFs to estimate the orientation and the position of the tool and a fuzzy expert system to identify when the tool fastens a bolt and which bolt was fastened. This paper also presents a tilt angle correction method using an IMU and a position sensor, and an orientation correction method using an IMU, a position sensor, and workpiece information. Experimental results to validate the proposed methods are also presented.

II. OVERVIEW

A string-encoder position sensor provides the location of the center of mass of a tool, and an IMU provides the orientation of the tool. With this sensor configuration, the position of the tool tip can be calculated as

$$[x_t \quad y_t \quad z_t]^{\mathrm{T}} = [x_p \quad y_p \quad z_p]^{\mathrm{T}} + C_t^f [L_x \quad L_y \quad L_z]^{\mathrm{T}} \quad (1)$$

where x_t, y_t, and z_t represent the three position coordinate components of the calculated position of the tool tip with respect to the local fixed frame; x_p, y_p, and z_p represent the three position coordinate components of the center of mass of a tool with respect to the local fixed frame; C_t^f is a direction cosine matrix from the tool frame to the local fixed frame; and L_x, L_y, and L_z are the location components from the center of mass of the tool to the tip with respect to the tool frame. L_x, L_y, and L_z are fixed and can be predetermined. The direction cosine matrix is obtained by integrating angular velocity measurements from the gyros of an IMU. However, an IMU suffers from the following errors.

1) Both accelerometers and gyros have white noise and nonlinearity.
2) Gyros have small random walk.

In order to compensate for the errors of an IMU, an intelligent system which utilizes KFs and a fuzzy expert system is proposed. Fig. 1 shows the structure of the proposed system. An IMU consists of accelerometers and gyros that have biases and gain factors [23]. Thus, accelerometers and gyros should be calibrated. Since the position sensor consists of encoders which always start from zero whenever the sensor is turned on, it should be initialized by locating the sensor in a known location. One KF is used to estimate the orientation and the angular velocities of the tool through gyro measurements. Another KF is employed to estimate the positions and the accelerations of the center of mass of the tool. The workpiece information provides the locations and the orientations of all bolts. All the information is processed via an expert system to identify the fastened bolt and to correct the orientation error. When the system detects fastening action, the fastened bolt is identified. Then, the orientation error is corrected using the location and the orientation of the fastened bolt and the position sensor location. When the tool is stationary, the tilt angles of the tool are corrected by using the gravity vector measured by accelerometers. The fuzzy expert system outputs the orientation

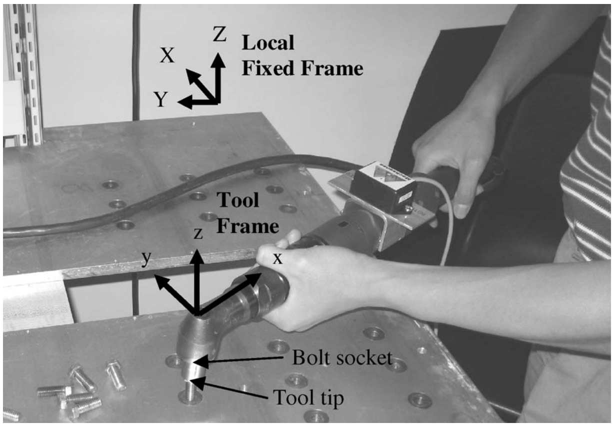

Fig. 2. Local fixed frame and the tool frame: The Z-axis of the local fixed frame is the opposite direction of the gravity vector, and the z-axis of the tool frame is along the bolt socket axis.

and the position of the center of mass of the tool. Then, the location of the tool tip is estimated using (1).

III. Attitude Estimation

A. Quaternions

The quaternion attitude representation is widely used to find the orientation of the body frame with respect to the local fixed frame. Quaternion representation obtains a direction cosine matrix with a single rotation with respect to an axis [24]. The direction cosine matrix from the tool frame to the local fixed frame (C_t^f) can be represented with the quaternion attitude representation as follows:

$$\begin{aligned} C_t^f &= \begin{bmatrix} c_{Xx} & c_{Yx} & c_{Zx} \\ c_{Xy} & c_{Yy} & c_{Zy} \\ c_{Xz} & c_{Yz} & c_{Zz} \end{bmatrix} \\ &= \begin{bmatrix} q_0^2+q_1^2-q_2^2-q_3^2 & 2(q_1q_2-q_0q_3) & 2(q_1q_3-q_0q_2) \\ 2(q_1q_2+q_0q_3) & q_0^2-q_1^2+q_2^2-q_3^2 & 2(q_2q_3+q_0q_1) \\ 2(q_1q_3-q_0q_2) & 2(q_2q_3+q_0q_1) & q_0^2-q_1^2-q_2^2+q_3^2 \end{bmatrix} \end{aligned} \tag{2}$$

where q_0, q_1, q_2, and q_3 are the quaternion components that satisfy

$$q_0^2 + q_1^2 + q_2^2 + q_3^2 = 1. \tag{3}$$

B. Orientation KF

Gyros measure angular velocities with respect to the inertial frame which has its origin at the center of the Earth, and its axes are stationary with respect to the fixed stars [24]. However, the tool tracking system is used in a small area, and the local fixed frame is attached to a stationary building which rotates 360°/day with the Earth. Thus, the position and orientation changes due to the orientation of the Earth should be discarded. In order to discard the angular velocity of the Earth, gyros are calibrated so that the angular velocity is zero when the IMU is stationary with respect to the local fixed frame. Fig. 2 shows the tool and local fixed frames which are attached to the lab building. Fig. 2 also shows that the Z-axis of the local fixed frame is chosen in the opposite direction of the local gravity vector, and the z-axis of the tool frame is chosen so that it is parallel to the bolt socket axis, which is parallel to the fastened bolt.

To design a KF, consider the following state-space model of a linear time-invariant system in continuous time:

$$\dot{x} = \mathbf{F} \cdot x + \mathbf{G} \cdot u + w \tag{4}$$

$$y = \mathbf{H} \cdot x + e \tag{5}$$

where x is the state, $\mathbf{F}$ is the dynamic system matrix, $\mathbf{G}$ is the system input matrix, u is the deterministic input, w is the process noise, y is the measurements, $\mathbf{H}$ is the measurement matrix, and e is the measurement noise. In discrete time domain, (4) and (5) are written as

$$x_k = \mathbf{\Phi} \cdot x_{k-1} + \mathbf{\Gamma} \cdot u_{k-1} + w_{k-1} \tag{6}$$

$$y_k = \mathbf{H} \cdot x_k + e_k \tag{7}$$

where x_k is the state at time k, $\mathbf{\Phi}$ is the dynamic system matrix, $\mathbf{\Gamma}$ is the system input matrix, u_{k-1} is the deterministic input at time $k-1$, w_{k-1} is the process noise at time $k-1$, y_k is the measurements at time k, and e_k is the measurement noise at time k. To utilize the Kalman filtering method, the quaternion equation should be written in the form of (4). The differential equation of quaternion q with respect to time has the following matrix form:

$$\begin{bmatrix} \dot{q}_0 \\ \dot{q}_1 \\ \dot{q}_2 \\ \dot{q}_3 \end{bmatrix} = \frac{1}{2} \begin{bmatrix} q_0 & -q_1 & -q_2 & -q_3 \\ q_1 & q_0 & -q_3 & q_2 \\ q_2 & q_3 & q_0 & -q_1 \\ q_3 & -q_2 & q_1 & q_0 \end{bmatrix} \cdot \begin{bmatrix} 0 \\ \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} \tag{8}$$

where ω_x, ω_y, and ω_z are the instantaneous angular velocity components of the fastening tool in each axis. Since there are four quaternion states and three angular velocity measurements, the state of orientation x_{ori} becomes

$$x_{\mathrm{ori}} = [q_0 \quad q_1 \quad q_2 \quad q_3 \quad \omega_x \quad \omega_y \quad \omega_z]^{\mathrm{T}}. \tag{9}$$

From (8), the system dynamic matrix of orientation becomes

$$\mathbf{\Phi}_{\mathrm{ori}} = \frac{1}{2} \begin{bmatrix} 2 & 0 & 0 & 0 & -q_1 \cdot t & -q_2 \cdot t & -q_3 \cdot t \\ 0 & 2 & 0 & 0 & q_0 \cdot t & -q_3 \cdot t & q_2 \cdot t \\ 0 & 0 & 2 & 0 & q_3 \cdot t & q_0 \cdot t & -q_1 \cdot t \\ 0 & 0 & 0 & 2 & -q_2 \cdot t & q_1 \cdot t & q_0 \cdot t \\ 0 & 0 & 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 2 \end{bmatrix} \tag{10}$$

where t is the sampling time. The system input matrix of orientation $\mathbf{\Gamma}_{\mathrm{ori}}$ is a zero matrix because the tool is rotated by a human operator. Since the quaternion states are estimated from the angular velocities, the process noise of the system is

$$w_{k-1,\mathrm{ori}} = w_{\mathrm{ang}} \cdot [0 \quad 0 \quad 0 \quad 0 \quad 1 \quad 1 \quad 1]^{\mathrm{T}} \tag{11}$$

where w_{ang} is the process noise of the angular velocity of the tool. Since angular velocities are measured using calibrated gyros, the measurement matrix of orientation is

$$\mathbf{H}_{\mathrm{ori}} = [0_{3\times 4} \quad I_{3\times 3}]. \tag{12}$$

To satisfy (3), the quaternion components should be normalized after they are determined.

The rank of the observability matrix is calculated to check the estimation accuracy. The states of a KF converge on meaningful estimations when the states are observable [25]. The observability matrix $(\mathbf{OM})$ is calculated as

$$\mathbf{OM} = \begin{bmatrix} \mathbf{H} \\ \mathbf{H}\cdot\mathbf{F} \\ \vdots \\ \mathbf{H}\cdot\mathbf{F}^{m-1} \end{bmatrix} \tag{13}$$

where m is the dimension of the state vector $\boldsymbol{x}$. If the observability matrix has a rank of m, then the states are completely observable.

For the orientation KF, the rank of the observability matrix is three, and only three angular velocities are observable. In other words, the quaternion terms may not converge to the correct values. Therefore, a quaternion term correction method needs to be implemented. The details of this method will be discussed in the expert system section.

IV. Position Estimation of the Center of Mass of the Tool

A. Motion Equations Using an IMU

Since accelerometers measure accelerations with respect to the inertial frame, the motion equations using accelerometers are derived from the inertial frame. However, the local fixed frame is attached to a stationary building, which, in fact, moves with respect to the inertial frame in this application. Therefore, the equation of motion should be written with respect to the local fixed frame. The acceleration of an object with respect to the local fixed frame can be expressed as [24]

$$\dot{V}^f = A^f - (2\cdot\omega_e + \omega_{ef}) \times V^f - \omega_e \times [\omega_e \times R]^f + g^f \tag{14}$$

where V is the velocity of the tool, A represents the specific force acceleration, superscript f represents the local fixed frame, ω_e represents the angular velocity of the Earth, ω_{ef} is the turn rate of the local fixed frame with respect to the Earth frame, R is the location of the tool from the center of the Earth, and g is the gravity vector. In this application, ω_{ef} is zero because the local fixed frame is attached to a stationary building which rotates with the Earth. The centripetal force term $\omega_e \times [\omega_e \times R]$ is caused by the angular velocity of the Earth and changes as R changes. However, since the change of R is very small compared to R in this application, this centripetal force is considered constant. Combining the centripetal force with the gravitational force results in different local gravity values. This local gravity can be written as

$$g_l^f = g^f - \omega_e \times [\omega_e \times R]^f. \tag{15}$$

The Coriolis force $2\cdot\omega_e \times V^f$ can be ignored when the velocity of the object is small because the angular velocity of the Earth is 7.3×10^{-5} rad/s. Since the velocity of the tool is usually less than 1 m/s in this application, the Coriolis term is much lower than the noise level of the accelerometers; hence, this term is ignored. Then, (14) can be simplified as

$$\dot{V}^f = A^f + g_l^f. \tag{16}$$

The specific force acceleration is represented with respect to the tool frame using accelerometers. In order to change the specific force acceleration terms from the tool frame to the local fixed frame, a direction cosine matrix is required. Thus, (16) is rewritten as

$$\dot{V}^f = C_t^f A^t + g_l^f. \tag{17}$$

The direction cosine matrix from the tool frame to the local fixed frame can be determined from (2). Since the Z-axis of the local fixed frame is chosen in the opposite direction of the local downward, the local gravity vector is expressed as

$$g_l^f = [0 \quad 0 \quad -|g_l|] \tag{18}$$

where $|g_l|$ is the magnitude of the local gravity vector.

B. Position KF

For the position estimating system, six measurements are available: three position components in the local fixed frame from the position sensor and three acceleration components in the tool frame from the IMU. From (17) and (18), the three acceleration measurements in the tool frame can be expressed in the local fixed frame in the form of (4) as

$$\begin{aligned} \dot{V}_x &= c_{Xx}\cdot A_x + c_{Yx}\cdot A_y + c_{Zx}\cdot A_z \\ \dot{V}_y &= c_{Xy}\cdot A_x + c_{Yy}\cdot A_y + c_{Zy}\cdot A_z \\ \dot{V}_z &= c_{Xz}\cdot A_x + c_{Zy}\cdot A_y + c_{Zz}\cdot A_z - |g_l| \end{aligned} \tag{19}$$

where V_x, V_y, and V_z are the velocity components in each axis, and A_x, A_x, and A_x, are the acceleration measurement components in each axis. The velocity equations become

$$\begin{aligned} \dot{P}_x &= V_x \\ \dot{P}_y &= V_y \\ \dot{P}_z &= V_z \end{aligned} \tag{20}$$

where P_x, P_y, and P_z are the position components in each axis. According to (19) and (20), the state of the position KF, x_{pos}, is defined as follows:

$$x_{\mathrm{pos}} = [P_x \quad V_x \quad A_x \quad P_y \quad V_y \quad A_y \quad P_z \quad V_z \quad A_z]^{\mathrm{T}}. \tag{21}$$

The position and velocity components are represented in the local fixed frame, and the acceleration components are represented in the tool frame. From (19) and (20), the system

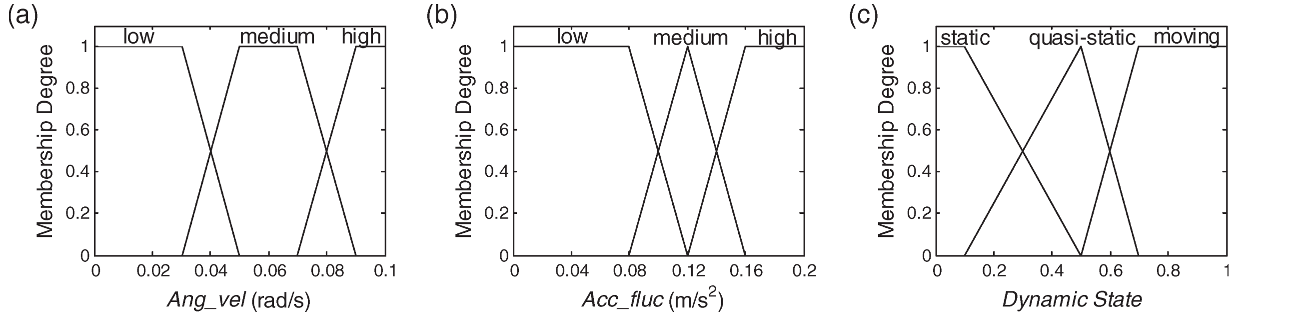

Fig. 3. Membership functions of the fuzzy expert system for the tilt angle correction algorithm. (a) Magnitude of angular velocity. (b) Acceleration fluctuation. (c) Dynamic state.

dynamic matrix of the object position in discrete time, $\mathbf{\Phi}_{\mathrm{pos}}$, becomes

$$\mathbf{\Phi}_{\mathrm{pos}} = \begin{bmatrix} 1 & t & c_{Xx}\cdot t^2/2 & 0 & 0 & c_{Yx}\cdot t^2/2 & 0 & 0 & c_{Zx}\cdot t^2/2 \\ 0 & 1 & c_{Xx}\cdot t & 0 & 0 & c_{Yx}\cdot t & 0 & 0 & c_{Zx}\cdot t \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & c_{Xy}\cdot t^2/2 & 1 & t & c_{Yy}\cdot t^2/2 & 0 & 0 & c_{Zy}\cdot t^2/2 \\ 0 & 0 & c_{Xy}\cdot t & 0 & 1 & c_{Yy}\cdot t & 0 & 0 & c_{Zy}\cdot t \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & c_{Xz}\cdot t^2/2 & 0 & t & c_{Yz}\cdot t^2/2 & 1 & t & c_{Zz}\cdot t^2/2 \\ 0 & 0 & c_{Xz}\cdot t & 0 & 0 & c_{Yz}\cdot t & 0 & 1 & c_{Zz}\cdot t \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}. \tag{22}$$

The gravitational force is treated as a deterministic input. Since the Z-axis is parallel to the gravity vector, the velocity and position changes due to the gravity vector should be compensated in the Z-axis. Thus, the system input matrix of position becomes

$$\mathbf{\Gamma}\cdot u_{k-1} = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & -|g_l|\cdot t^2/2 & -|g_l|\cdot t & 0 \end{bmatrix}^{\mathrm{T}}. \tag{23}$$

Since the position and velocity states are estimated from three accelerations, the process noise is

$$w_{k-1,\mathrm{pos}} = q_{\mathrm{accel}}\cdot [0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 1 \quad 0 \quad 0 \quad 1]^{\mathrm{T}} \tag{24}$$

where q_{accel} is the process noise of the tool acceleration.

The acceleration of each axis is measured by three accelerometers, and the position components are measured by a position sensor. Since both accelerometers and the position sensor are calibrated and initialized, the measurement matrix for the position estimation becomes

$$\mathbf{H}_{\mathrm{pos}} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}. \tag{25}$$

The rank of the observability matrix of the position KF is nine. Thus, all nine states are observable.

TABLE I
FUZZY RULES TO IDENTIFY THE STATIONARY STATE OF THE TOOL

Fuzzy Rules	*Ang_vel*	*Acc_fluc*	*Dynamic state*
1	Low	Low	Static
2	Low	Med	Quasi-static
3	Med	Low	Quasi-static
4	Others		Moving

V. Expert System

A. Tilt Angle Correction

The tilt angles of the tool can be measured with the three accelerometers of an IMU when the tool is stationary. To identify the stationary state, the relationship between the dynamic state of the tool and the state estimation from the sensor measurements is established. When the tool is stationary, the linear velocity of the tool is zero. In this case, the angular velocity measurement should be zero, the acceleration measurements in each axis should be constant, and the magnitude of acceleration measurements should be equal to the magnitude of the gravity vector. However, due to the random walk property and the noise of gyros, the angular velocity measurements may not be zero when the tool is stationary. In addition, the acceleration measurements contain noise, and the magnitudes of the acceleration measurements due to gravity vary, depending on the tilt angles, because of the nonlinearity property of accelerometers. To identify the stationary state of the tool, the following three sets of states are used: 1) angular velocity; 2) acceleration fluctuation; and 3) linear velocity. The estimations of accelerations and angular velocities from the KFs are used instead of the direct measurements from the IMU because the estimated values from the KFs have less noise. However, the derivatives of the position sensor outputs are used for the linear velocity calculation because they are zero when the tool is stationary.

Although the KFs are used to estimate acceleration and angular velocity states, only a portion of noise is removed, and the linear acceleration and angular velocity estimations still suffer from nonlinearity and random walk. To identify the stationary state from these inaccurate measurements, a fuzzy expert system is proposed. The rules are identified based on the properties of the sensors using linguistic terms. Let the magnitude of angular velocity (Ang_vel) of the tool be expressed as

$$Ang\_vel = \left(\omega_x^2 + \omega_y^2 + \omega_z^2\right)^{0.5}. \tag{26}$$

TABLE II
RULES FOR THE FASTENING TOOL TRACKING SYSTEM IN LINGUISTIC TERMS

Rule 1: Stationary State Identification	
Rule 1-1	IF the derivative of the position sensor output is zero for the last 0.1 second AND *dynamic state* < 0.5 for the last 0.1 second, THEN update the average accelerations AND the tool is stationary.
Rule 1-2	IF the tool was stationary in the previous time step AND the derivative of the position sensor output is zero AND *dynamic state* < 0.5, THEN update the average accelerations AND the tool is stationary.
Rule 1-3	IF the tool is stationary, THEN $\omega_x = \omega_y = \omega_z = 0$ AND correct the quaternion terms based on the average accelerations.
Rule 2: Fastening Action Detection	
Rule 2-1	IF *Acc* > 20 m/s^2 AND *fastening_period* > 0.1 second THEN *fastening_period* = 0 AND peak = 0 AND peak_high = 1.
Rule 2-2	IF *Acc* > 20 m/s^2, THEN peak_high = 1
Rule 2-3	IF *Acc* < 20 m/s^2 AND peak_high = 1 THEN peak = peak +1 AND peak_high = 0
Rule 2-4	IF peak = 3 AND *fastening_period* < 0.1 second, THEN the tool is fastening a bolt.
Rule 3: Fastened Bolt Identification	
Rule 3-1	IF the tool is fastening a bolt AND there is only one bolt that satisfies $PSE_n \leq MPS + MME$, THEN the tool is fastening the nth bolt.
Rule 3-2	IF the tool is fastening a bolt AND there are more than one bolt that satisfies $PSE_n \leq MPSE + MME$, THEN the bolt with the maximum Bolt_Output_1 membership value is being fastened.
Rule 3-3	IF the tool is fastening a bolt AND there is more than one bolt that has the highest Bolt_Output_1 membership value AND all the bolts were fastened except one bolt, THEN the tool is fastening the unfastened bolt.
Rule 3-4	IF the tool is fastening a bolt AND there is more than one bolt that has the highest Bolt_Output_1 membership value AND more than one bolt is not fastened before, THEN assume that the bolt with the maximum Bolt_Output_2 membership value is being fastened. IF the next fastening action is detected, THEN identify the fastened bolt AND identify which bolt was fastened previously
Rule 3-5	IF the fastened bolt is identified THEN correct the quaternion terms

When the tool is stationary, the fluctuations of acceleration estimation in each axis should be lower than the maximum noise of each axis after Kalman filtering. The acceleration fluctuation in each measurement is expressed as one acceleration measurement less the average acceleration of the stationary state. The average acceleration of the stationary state in each axis is expressed as

$$
\begin{aligned}
Avg\_A_x &= \sum_{i=1}^{s} A_x(i)/s \\
Avg\_A_y &= \sum_{i=1}^{s} A_y(i)/s \\
Avg\_A_z &= \sum_{i=1}^{s} A_z(i)/s
\end{aligned} \tag{27}
$$

where s is the number of acceleration measurement samples. The sample size increases as the duration of the stationary state of the tool increases. The acceleration fluctuation (Acc_fluc) is defined as

$$
Acc\_fluc = \left((A_x - Avg\_A_x)^2 + (A_y - Avg\_A_y)^2 + (A_z - Avg\_A_z)^2\right)^{0.5}. \tag{28}
$$

The fuzzy sets of the expert system inputs are shown in Fig. 3(a) and (b). Fig. 3(c) shows the dynamic states of the tool. Table I lists the fuzzy rules to identify the stationary state of the tool.

When the derivative of the position sensor is zero for 0.1 s and the *dynamic state* is less than 0.5 for 0.1 s, the tool is considered stationary. The 0.1 s period was chosen because it is not realistic for an operator to move a tool so that the *dynamic state* is less than 0.5 and the derivative of the encoder output is zero for 0.1 s unless the tool is stationary. The 0.1 s period was also used to find the average accelerations in each axis. Based on the aforementioned assumption, the fuzzy expert rules for the stationary state identification of a tool are shown in Table II (Rules 1-1 and 1-2).

When the system concludes that the tool is stationary, it corrects the tilt angles. To correct the tilt angles, the relationship between the tilt angles and the direction cosine matrix is established. Since the Z-axis of the local frame is chosen to be parallel to the gravity vector, the tilt angle components of the direction cosine matrix from (2) are c_{Xz}, c_{Yz}, and c_{Zz}. When the tool is stationary, the tilt angle components of the tool can be determined from the acceleration measurements. Since $c_{Xx}^2 + c_{Yz}^2 + c_{Zz}^2 = 1$, the tilt angle components can be derived by normalizing the acceleration components as follows:

$$
\begin{aligned}
c_{Xz} &= Avg\_A_x / \left(Avg\_A_x^2 + Avg\_A_y^2 + Avg\_A_z^2\right) \\
c_{Yz} &= Avg\_A_y / \left(Avg\_A_x^2 + Avg\_A_y^2 + Avg\_A_z^2\right) \\
c_{Zz} &= Avg\_A_z / \left(Avg\_A_x^2 + Avg\_A_y^2 + Avg\_A_z^2\right).
\end{aligned} \tag{29}
$$

To reduce the acceleration noise, the average accelerations are used to calculate the tilt angles in (29). From (2), the quaternion terms in tilt angles are

$$
\begin{aligned}
2(q_1 q_3 - q_0 q_2) &= c_{Xz} \\
2(q_2 q_3 + q_0 q_1) &= c_{Yz} \\
q_0^2 - q_1^2 - q_2^2 + q_3^2 &= c_{Zz}.
\end{aligned} \tag{30}
$$

Although there are four equations, three from (30) and one from (3), with four unknowns, it is not possible to correct all four quaternion terms because all four equations are in nonlinear forms. However, since the tool orientation is constantly corrected as mentioned in Section II, the errors of the quaternion terms are small. Thus, one of the four quaternion terms is assumed correct, and the other three terms are corrected. Since there are four possibilities of correction, all four cases are evaluated. The corrected terms are first evaluated using (3).

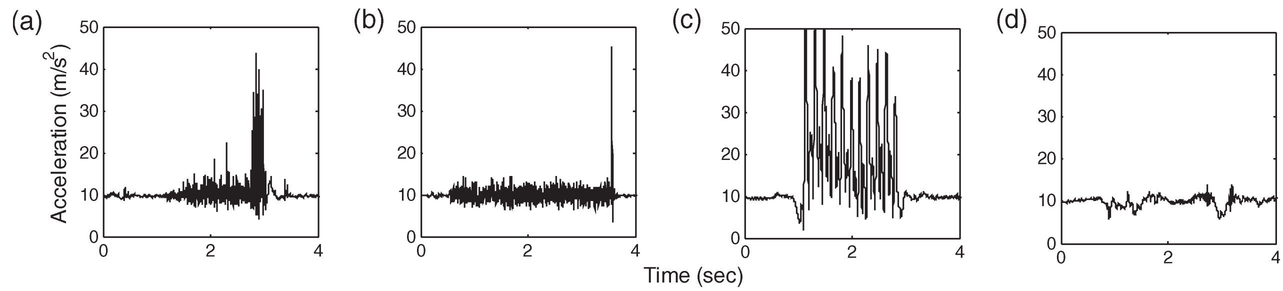

Fig. 4. Possible acceleration signatures of the fastening tool used in different scenarios. (a) Fastening action. (b) Base excitation. (c) Hand vibration. (d) Normal movements.

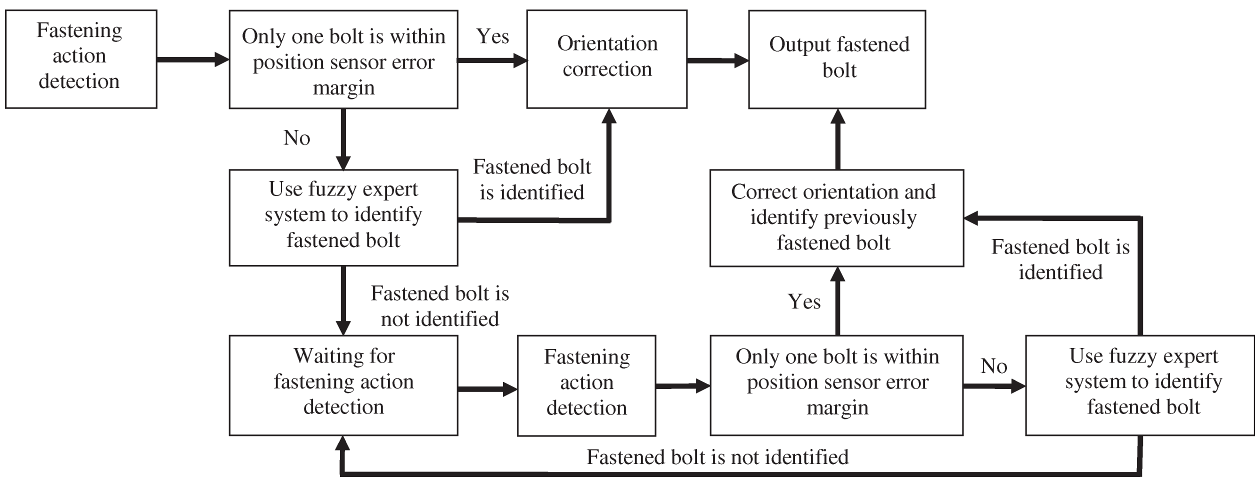

Fig. 5. Fastened bolt identification process.

The corrected terms that satisfy (3) with very small error were considered as the correct solutions. From the correct solutions, the one with the minimum root-mean-square error is chosen as the best fit because it requires the minimum change of orientation. When the tool is stationary, the angular velocity of the tool is set to zero (Rule 1-3 in Table II).

B. Fastening Action Detection

To identify a fastening action, the acceleration signature is studied and distinguished from other possible movements that the fastening tool can experience (Fig. 4). The acceleration signature of fastening action [Fig. 4(a)] shows very high vibration and high magnitude of acceleration. Fig. 4(b) shows the base excitation when the tool is free running in the air without fastening a bolt. The acceleration of the base excitation has a high frequency of vibration, but it does not have a high magnitude of acceleration. Fig. 4(c) shows the situation when the tool is shaken by a person. It shows high magnitudes of acceleration but does not show a high frequency of vibration. Fig. 4(d) shows normal movements when the tool is moved around. This movement does not have a high frequency of vibration or high peaks of acceleration. This paper shows that fastening action can be identified with acceleration frequency contents and the magnitudes of acceleration. Let the magnitude of acceleration measurement (Acc) be

$$Acc = \left(A_x^2 + A_y^2 + A_z^2\right)^{0.5}. \tag{31}$$

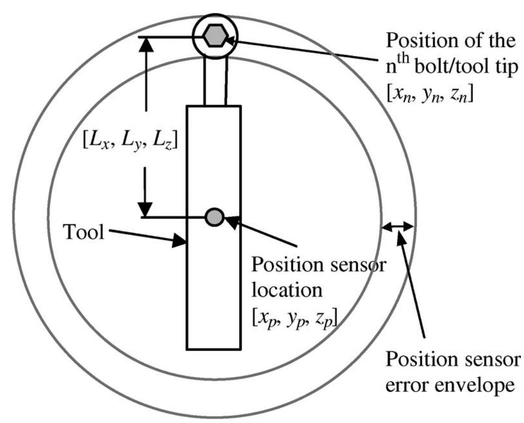

Fig. 6. Position sensor error envelope while a tool fastens a bolt. The position of the tool tip coincides with one of the bolts.

If at least three peaks satisfy $Acc > 20$ m/s^2 within 0.1 s interval, the expert system concludes that the tool is fastening a bolt. In order to measure the 0.1 s interval, a time variable $fastening\_period$ is initialized when the accelerometers first detect $Acc > 20$ m/s^2 and increases as the time elapses. If the system does not detect three peaks that satisfy $Acc > 20$ m/s^2 within 0.1-s interval, it will be initialized again when the next peak is detected. The rules for the fastening action detection are shown in Table II (Rules 2-1 to 2-4). The specific values of the expert system conditions such as the peak values of Acc can vary, depending on the shapes and the materials of the bolt and the workpiece.

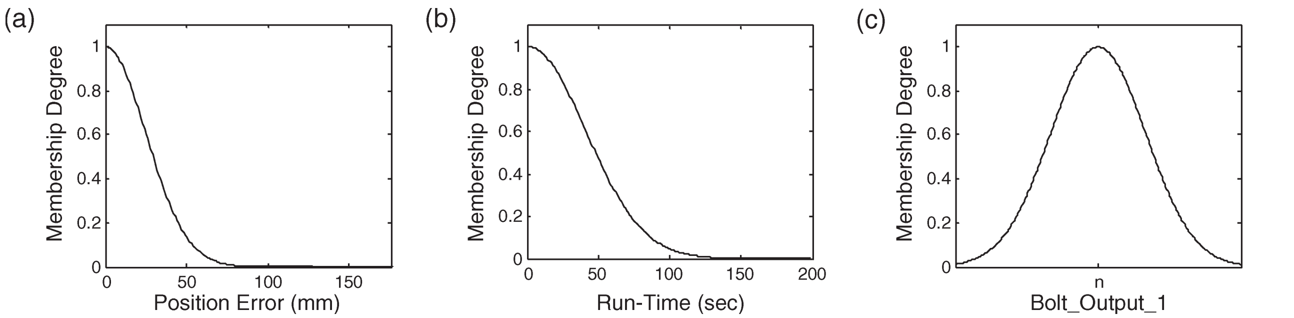

Fig. 7. Membership degree functions of the (a) calculated tool tip position error, (b) run time, and (c) output for Bolt "n."

C. Fastened Bolt Identification

When a fastening action is detected, the tool tracking system should identify the fastened bolt. The fastened bolt identification process is summarized in Fig. 5. There are three scenarios for the bolt identification.

1) The position sensor alone identifies the fastened bolt.
2) When scenario 1) fails, the orientation of the tool is used to verify the fastened bolt.
3) When scenario 2) fails, the system assumes that the bolt with the highest probability of being fastened is fastened and waits for the next fastening action. When the system identifies the next fastened bolt, it identifies which bolt was fastened previously.

When the system successfully identified the fastened bolt, it corrects the orientation error and outputs the fastened bolt number.

When the tool fastens a bolt, the location of the tool tip coincides with one of the bolts (Fig. 6). Then, the distance between the position sensor and one of the bolt position should be $(L_x^2 + L_y^2 + L_z^2)^{0.5}$. However, the position sensor has error, and the location of the bolt also has error due to manufacturing uncertainties. When the tool fastens a bolt, the position sensor error with respect to the n^{th} bolt is

$$PSE_n = \left((x_n - x_p)^2 + (y_n - y_p)^2 + (z_n - z_p)^2\right)^{0.5} - \left(L_x^2 + L_y^2 + L_z^2\right)^{0.5} \quad (32)$$

where PSE_n represents the position sensor error of the n^{th} bolt, and x_n, y_n, and z_n represent the three position coordinate components of the n^{th} bolt. The value of PSE_n includes the error of the position sensor, as well as the manufacturing error of the workpiece. Thus, when the tool fastens a bolt, the following inequality holds for at least one bolt:

$$PSE_n \le MPSE + MMU \quad (33)$$

where $MPSE$ represents the maximum position sensor error, and MMU represents the maximum manufacturing uncertainties. If there is only one bolt that satisfies (33), the system concludes that the tool fastens that bolt.

It is possible that (33) is satisfied for more than one bolt. In this case, the tool tip position calculation using (1) is utilized to identify the fastened bolt. However, identifying fastened bolt does not simply correspond to finding the closest bolt from the calculated tool tip position because the orientation error is unknown. To identify the fastened bolt in the presence of growing orientation uncertainties, the fuzzy expert system is utilized. Two inputs are used to identify the fastened bolt: the calculated tool tip position error and the run time, which is the duration from the previous complete orientation correction to the current time excluding the stationary state period. As the calculated tool tip position error with respect to a bolt gets smaller, the probability of fastening the bolt gets higher. The calculated tool tip position error is represented as

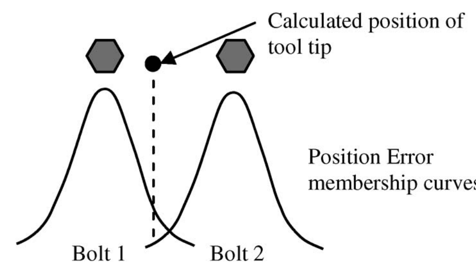

Fig. 8. Fastened bolt identification when the calculated tool tip position error is the determining factor.

$$PE_n = \left((x_t - x_n)^2 + (y_t - y_n)^2 + (z_t - z_n)^2\right)^{0.5}. \quad (34)$$

As the run time increases, the reliability of the calculated tool tip position decreases. Both position error and run time are modeled, and the membership degrees with respect to the n^{th} bolt are shown in Fig. 7. In this application, the maximum error of the tool is 179 mm because the position sensor was located 165 mm from the tool tip and the maximum position sensor error was ± 7 mm. The two antecedent conditions are aggregated with the min operator [18], [26] to get the implication on the consequence membership function. Fig. 7(c) shows the membership degree output for the n^{th} bolt. The bolt with the highest membership degree of Bolt_Output_1 is chosen as the fastened bolt because it has the highest probability of being fastened. When the membership degree of calculated tool tip position error is lower than that of run time, the closest bolt from the calculated tool tip position is the fastened bolt, as shown in Fig. 8.

However, if run time becomes the determining factor, more than one bolt can have the highest membership degree in Bolt_Output_1 fuzzy set. If all bolts were fastened except for one, the system concludes that the unfastened bolt is now being

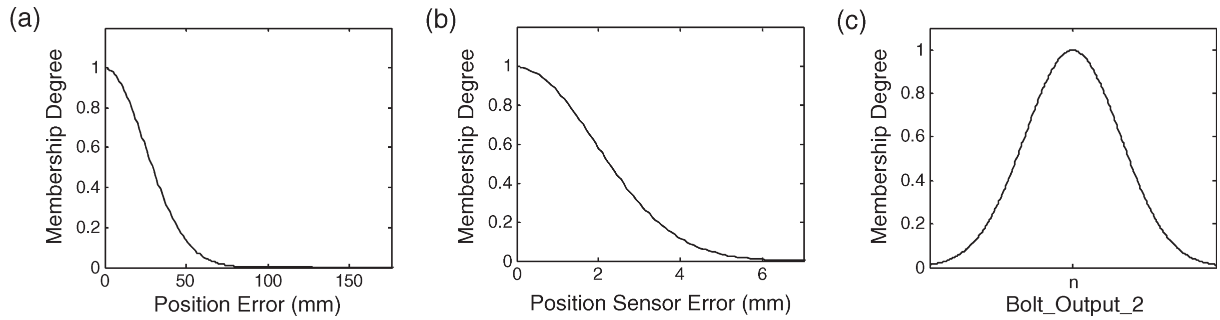

Fig. 9. Membership degree functions of the (a) calculated tool tip position error, (b) position sensor error, and (c) output for Bolt "n."

fastened. If more than one bolt is not fastened before, the system cannot identify which bolt is being fastened. Then, the system uses another fuzzy expert system to identify the bolt with the highest probability of being fastened using position error and position sensor error (Fig. 9). The two antecedent conditions are multiplied to get the membership degree of Bolt_Output_2 for the n^{th} bolt, and the bolt with higher membership degree is assumed fastened. In this scenario, the fastening system also examines the next fastened bolt to ensure that the output of the fuzzy expert system is the correct fastened bolt. When the next fastening action is detected, the system identifies which bolt is currently fastened and finds the path from the fastened bolt to the previous fastened bolt with respect to the previous possible bolt positions and orientations. By comparing the distances and the orientations between the possible previous bolts and the next bolt, the system can identify which bolt was previously fastened. The expert rules for the fastened bolt identification phase are shown in Table II (Rules 3-1 to 3-4).

D. Orientation Correction

When a tool fastens a bolt, the orientation of the bolt and the vector, which connects the position sensor and the tool tip, is known. Since two vectors are known, the complete orientation of the tool can be determined. The tool frame is chosen so that the z-axis is parallel to the socket, which is almost parallel to the fastened bolt when the tool fastens a bolt. This axis gives the Z-axis vector of the direction cosine matrix: $\boldsymbol{c}_{Zx}$, $\boldsymbol{c}_{Zy}$, and $\boldsymbol{c}_{Zz}$. If the tool frame is selected so that L_y is zero, then the location of the tool tip with respect to the center of mass expressed in the tool frame becomes $[L_x \quad 0 \quad L_z]$. Then, from (1), the X-axis vector of the direction cosine matrix becomes

$$\begin{aligned}\boldsymbol{c}_{Xx} &= (x_t - c_{Zx}L_z - x_p)/L'_x\\ \boldsymbol{c}_{Xy} &= (y_t - c_{Zy}L_z - y_p)/L'_x\\ \boldsymbol{c}_{Xz} &= (z_t - c_{Zz}L_z - z_p)/L'_x \end{aligned} \tag{35}$$

where $L'_x = (x_t - c_{Zx}L_z - x_p)^2 + (y_t - c_{Zy}L_z - y_p)^2 + (z_t - c_{Zz}L_z - z_p)^2$. L'_x is used to normalize the X-axis vector of the direction cosine matrix instead of L_x. This is attributed to the fact that L_x may not match L'_x due to the position sensor error (PSE_n). The Y-axis vector of the direction cosine matrix can be calculated from the cross product of the two vectors of the direction cosine matrix. When all three vectors of the direction cosine matrix are determined, three tool frame vectors of the direction cosine matrix are normalized. Then, four quaternion terms can be determined from the direction cosine matrix. The corrected four quaternion terms are normalized to satisfy (3).

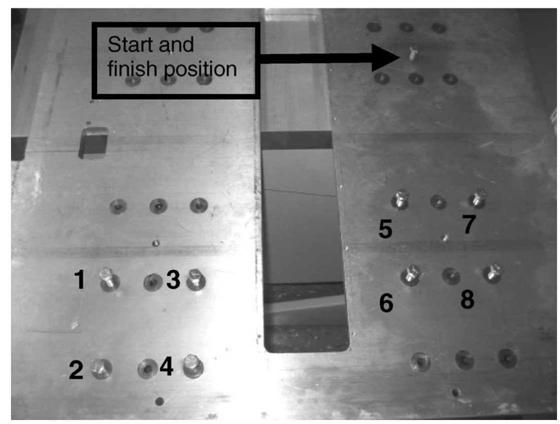

Fig. 10. Test bed for the laboratory experiment.

VI. Experiments

The fastening tool tracking system consists of a position sensor (3-D sensor, SpaceAge Control, Inc.) and a MEMS IMU (MDIMU-I-221-777, Mechworks Systems Inc.). The fastening tool tracking system is attached to a right angle tool and examined on a test bed shown in Fig. 10. Eight bolts are placed on the test bed. When the tool was positioned on Bolts 1, 4, 5, 6, and 7, the bolts were fastened, but when the tool was on Bolts 2, 3, and 8, the tool free ran in the air right above the bolts to test if the system can differentiate the two different scenarios. The tool started from the initial position and moved for 204 s before it was sent back to the initial position. The tool moved from Bolt 1 to Bolt 8 in sequence, and after Bolt 6 was fastened, the tool was left stationary for 80 s. The test results of tracking the tool tip are shown in Fig. 11.

Fig. 11(a) shows the trajectory of the calculated tool tip position with the intelligent system which includes the KFs and the fuzzy expert system. Fig. 11(b) shows the trajectory of the calculated tool tip position without the intelligent system. When the system detects a fastening action, a square mark with $*$ symbol is added to the calculated bolt position. Fig. 11(a) shows that Bolts 1, 4, 5, 6, and 7 were marked, indicating

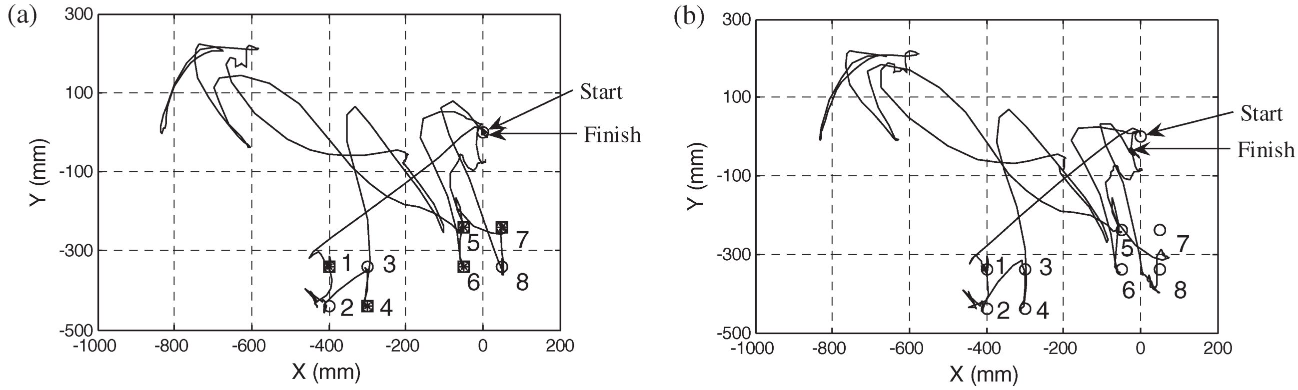

Fig. 11. Tool tracking results (a) with and (b) without the intelligent system.

TABLE III
POSITION ERROR COMPARISON BETWEEN WITH AND WITHOUT THE INTELLIGENT SYSTEM

Tool	Time	Position error with the intelligent system (mm)				Position error without the intelligent system (mm)			
position	(sec)	X-axis	Y-axis	Z-axis	Total	X-axis	Y-axis	Z-axis	Total
Bolt 1	19	-2	0	6	6	-2	1	6	6
Bolt 4	43	-12	-6	-6	15	-10	-4	9	14
Bolt 5	85	-2	-8	2	8	-9	-5	37	38
Bolt 6	89	-4	-2	2	5	-8	-7	38	39
Bolt 7	184	3	-6	7	10	8	-58	28	65
Finish	204	-1	-6	0	6	-27	-33	83	93

that the system successfully identified the fastened bolts. The start and finish points are almost identical when the intelligent system was used. However, Fig. 11(b) shows that the finish point is different from the start point when the tool tip position is calculated without the intelligent system. The calculated tool tip position errors with and without the intelligent system are summarized in Table III (with respect to the fastened bolt positions and the finish position). The total position errors of Table III were calculated using (34). The position error without the intelligent system increases over time because the orientation error drifts over time. However, the position error with the intelligent system shows that the error is reduced significantly because the error is corrected when the tool fastens a bolt and is stationary.

VII. CONCLUSION

This paper presented an intelligent tool tracking system that utilizes a hybrid sensor configuration consisting of an IMU and a position sensor. KFs were developed to estimate the orientation and the position of the tool more accurately. The outputs of the sensors are related to identify if the tool is stationary or fastening a bolt. When the tool is stationary, the system corrects the tilt angles. When the tool fastens a bolt, the system identifies the fastened bolt and corrects the orientation error. The intelligent system was validated through experiments.

In the experiment, the fastening tool tracking system was tested with a manufacturing assembly example in a laboratory setting. The position error increases as the time of operation elapses when the intelligent system was not used. However, by using the intelligent system, the experimental results show that the location of the fastened bolt can be correctly identified and the position error is reduced.

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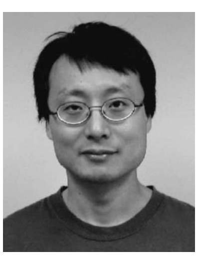

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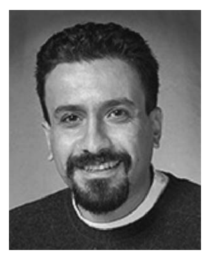

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