Evaluation of a Low-cost Inertial Dynamic Measurement System

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Abstract — **For a Parallel Kinematic Machine (PKM), encoders may be used to measure the relative change in length of the strut but they cannot detect any deformation of the strut due to thermal expansion and load. To obtain this type of data displacement should be directly measured for each strut. The use of inertial sensors provides a possible solution for the PKM strut length measurement. However, due to the dynamic characteristics of an inertial system and the effect of the machine tool environment, the inertial data contained bias error, misalignment and wide band random noise, and thus resulted in system position inaccuracy. In this paper, an inertial sensor based dynamic measurement system is introduced. Errors contained in the measurement system are analysed. To suppress the residual error which causing drifting error in position due to double integration process, an external measurement is used to estimate the system state variables through Kalman Filter data fusion. Results from these data processing methods applied are presented and analysed.**

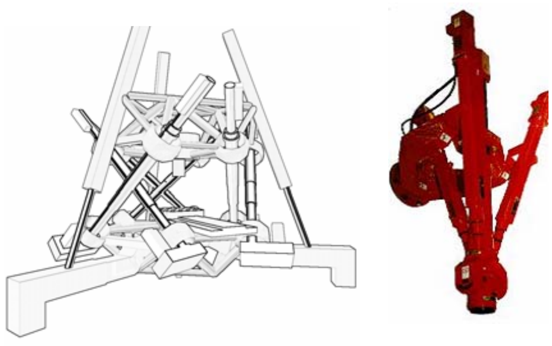
Keywords— **Inertial sensors, Parallel Kinematic Machine (PKM), Dynamic measurement, Signal processing, Kalman filtering, Estimation.**

I. INTRODUCTION

Inertial sensors are normally used in inertial navigation systems to provide vehicle guidance information. Inertial measurement involves measuring vehicle accelerations using accelerometers and angular velocity using gyroscopes. The main feature of inertial navigation systems (INS) is that they do not rely on the transmission or reception of external signals apart from the sensing of the physical motion of the vehicle. The self-contained, non-jammable, and autonomous properties make inertial systems particularly suitable for military navigation applications [1-3]. Today inertial navigation systems are used in all types of commercial and military aircraft, ships, tanks, submarines, missiles of all sizes, and space vehicle boosters [4].

In recent years, inertial sensors have been adopted for industrial robot applications and machine tool calibration [5, 6]. Accurately measuring of the position and orientation of a robot end-effector is the most critical issue for calibrating of robotic devices. Current robot system use the methods of theodolites, laser interferometers, vision systems, and coordinate measuring machines to acquire these measurements. These techniques require a large number of end-effector measurements and they are either too slow or overly expensive or both [7]. Furthermore, all of these systems impinge on the work envelope and thus make difficult, if not prohibit, their on-line use[8]. The Variax machine at the University of Nottingham, made by Giddings and Lewis Ltd, is such an example shown in Figure1(a). The Variax is a Parallel Kinematic Machine (PKM) which has the advantage of being more rigid, more agile and more accurate than that of traditional (serial link) machine tool structures [9-12]. Due to the use of the expensive laser interferometer for each parallel strut, the Variax machine can achieve about 12~14μm dynamic position accuracy [13]. Bur for the Tricept® TR600 shown in Fig.1(b), a hybrid parallel/serial structure robot, a prevalent encoder measurement device was used for each strut measurement. From data test results [14], the linear position error of the Tricept robot is about 0.62mm over a machine travel of 400mm, and this error is scalable over distance. Under certain circumstance, the Tricept robot has severe cutting deflection and could reach ±2.5mm. The main reason is that an encoder can only measure motor shaft or ball screw rotation when it is mounted on either the motor shaft or on the ball screw and convert to the relative change in length. It cannot measure any deformation of the structure caused by mechanical effects such as backlash, wear and thermal expansion. These errors in strut length measurement will be propagated to the pose of the PKM TCP (Tool Centre Point) through a forward kinematic model and result in a decrease of positional accuracy.

Since the accuracy of a machine tool solution is generally far higher than the required of a pure navigation system, high-grade inertial sensors are normally adopted to satisfy the high demand. Despite the advantages of an inertial measurement system, the high cost seriously limits the practical applications in the area if industrial robots and machine tools. However, the newly developed solid-state inertial sensors provide the possibility for these applications due to their advantages of being small size, low-cost, and self-contained [15-19]. In this work, a low-cost, solid-state inertial sensor was used for the dynamic position measurement of a PKM machine. The objectives are to investigate the application feasibility of an inertial system and develop a new approach to improve PKM strut length measurement by installing inertial sensors (an accelerometer and a gyroscope) to each strut (shown in Fig. 2), instead of use of the expensive laser interferometers.



a) Variax Machine b) Tricept TR600

Fig. 1 Structures of two typical PKMs with different strut length measurement methods: Variax using laser interferometers and Tricept using encoders

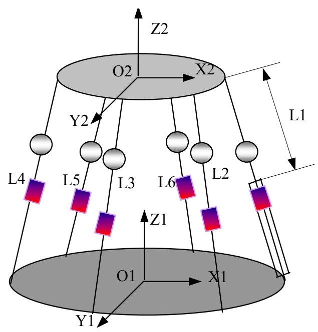


Fig. 2 Accelerometer and gyroscope mounted on each strut to measure the increment of strut length

In this paper, a low-cost inertial dynamical positioning system is introduced and evaluated. The system was implemented on the parallel kinematic machine (PKM) strut to provide the linear position measurement of the machine. Section II describes the inertial dynamic positioning system including the PKM strut measurement structure and the experimental setting. Section III performs the inertial system error analysis. In Section IV, an external measurement correction method through Kalman filtering is presented and some experimental results are shown and compared. Section V gives the evaluation and conclusions.

II. AN INERTIAL DYNAMIC MEASUREMENT SYSTEM

In order to investigate the feasibility and to understand the performance of inertial sensors applied for a PKM strut measurement, a simplified PKM strut rig was used as our experimental platform shown in Fig.3. In this work, a 8304B2 accelerometer was mounted on the strut and used to measure the strut movement. The change of the strut length can be obtained through a double numerical integration process. The proposed system comprised several modules: inertial measurement module, encoder measurement module and PKM strut motion module. For the inertial measurement module, it consists of a DC capacitive accelerometer, a 16-bit DAQ card, an amplifier or power supply to trim out offset of the accelerometer, and a 68-pin connection box. As the external measurement of the inertial system used in the Kalman filter, the encoder measurements (position or velocity) on PKM-Strut test bed were obtained through a Heidenhain lK121 counting card, which splits and output the motion signal. The PKM strut motion is controlled through the NextMove WorkBench software and the controller [20]. A Renishaw laser interferometer is used in the system to provide the reference position for the proposed inertial measurement system.

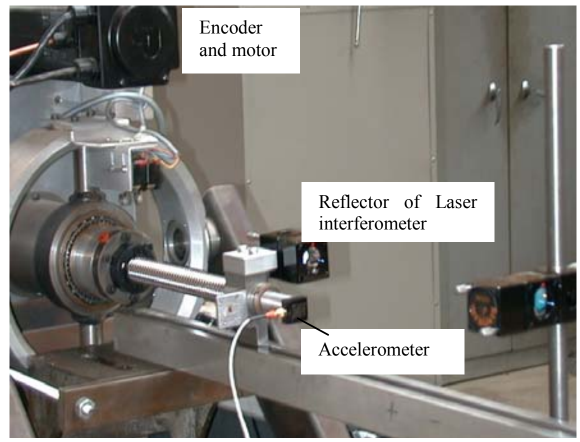


Fig. 3 Experimental setup for the PKM strut length measurement system

III. SYSTEM ERROR ANALYSIS

In an inertial measurement system, measurement errors are generally due to mechanical imperfections in the sensors and electrical imperfections in the associated instrumentation. These errors were categorized into three types: inertial sensor errors, misalignment error and computational process errors. Based on the system error analysis and determination, the measurement signal (a_{Mx}) from an accelerometer may be expressed in terms of an applied acceleration and measured error items as follows:

$$\frac{a_{Mx}}{K_{sf}} = a_{Rx} + \frac{1}{K_{sf}}(b_a + w) + S_y a_y + S_z a_z + e_{SF} + e_{gx} \qquad (1)$$

where a_{Rx} represents the real acceleration applied in the direction of the sensing axis; a_{Mx} represents the measured acceleration; K_{sf} is the scale factor of the accelerometer, or sensitivity; a_y and a_z are the accelerations applied perpendicular to the sensitive axis; S_y and S_z represents the cross-coupling factors; b_a is zero bias error (or offset error); e_{SF} is scale factor error caused by temperature's change; e_{gx} represents the misalignment error in initial position; w represents random noise.

In this work, the experimental work is carried out on a one-axis movement (x-axis), so the Equation (1) can be simplified as

$$a_{Rx} = \frac{1}{K_{sf}}(a_{Mx} - b_a - w) - e_{SF} - e_{gx} \tag{2}$$

Among these errors, the accelerometer bias error, the scale factor error and the misalignment error are predictable items and thus can be compensated for. If using a symbol to represent these predictable error items $\delta a_p = \frac{1}{K_{sf}} b_a + e_{SF} + e_{gx}$, we can get:

$$a_{Rx} = \frac{1}{K_{sf}}(a_{Mx} - w) - \delta a_p \tag{3}$$

The incremental velocity and position can then be obtained by integrating Equations (3):

$$V_{Rx} = V_{Mx} - \delta a_p t - \frac{1}{K_{sf}} \int w dt \tag{4}$$

$$P_{Rx} = P_{Mx} - \frac{1}{2}\delta a_p t^2 - \frac{1}{K_{sf}} \iint w dt \tag{5}$$

where, V_{Rx} and P_{Rx} represents the real velocity and position along the direction of the sensing x-axis; V_{Mx} and P_{Mx} represents the measured velocity and position along x-axis; $\int w dt$ and $\iint w dt$ is the once and twice integral to the random error.

From Equations (3) to (5), the term of δa_p causes error in velocity growing linearly with time, and causes error in position growing quadratically with time. Errors in acceleration are amplified through integration process and cause an offset in the derived velocity and a drifting error in the position. Therefore, it is important for the inertial system to compensate for acceleration errors and thus curb errors increasing in the velocity and position.

For the random error item, it contains noise and vibration changeable to the dynamic environment, and also involves variations in bias and scale factor due to temperature's change. These random errors appeared in a wide-band range, overlapped with the signal of interest and cannot be easily compensated for. Through the double integration used in the inertial position system the random error portion $\iint w dt$ in Equations(5) will cause a growing error term known as Random Walk [3]. This integration process deteriorated the inertial position accuracy since the signal of the strut motion is in a low frequency range and is contaminated with noise. Fig.4 presents the Random Walk results from a series of zero-g signals after the predictable errors compensated, the random errors show a non-deterministic behaviour in the derived position data.

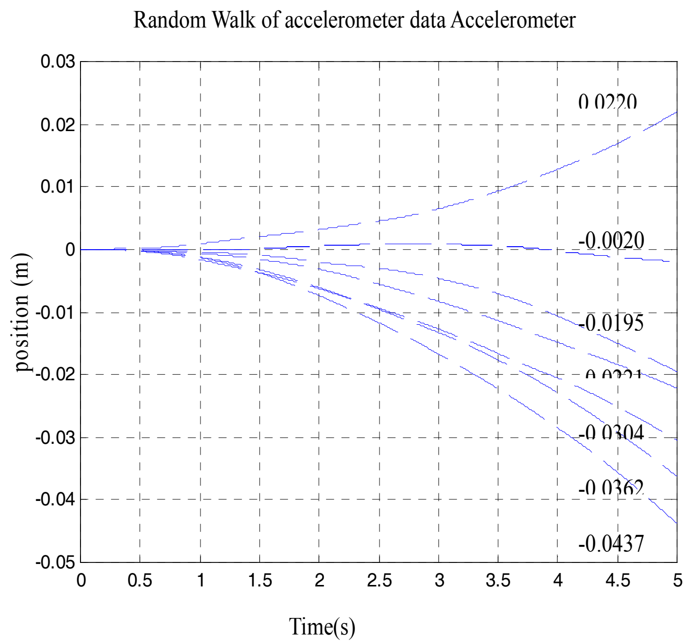


Fig.4 Random error in position by integrating several runs data measured in zero-g input

IV. EXTERNAL MEASUREMENT CORRECTION

As we know that errors in the sensed measurement are processed in the same algorithms as the error-free component of the sensor output. Even a slight offset error can cause large position error which building up over time. Therefore error reduction and correction methods must be developed to minimise error effects and improve system accuracy. Fig.5 shows the inertial measurement system error components and the corresponding error reduction methods applied.

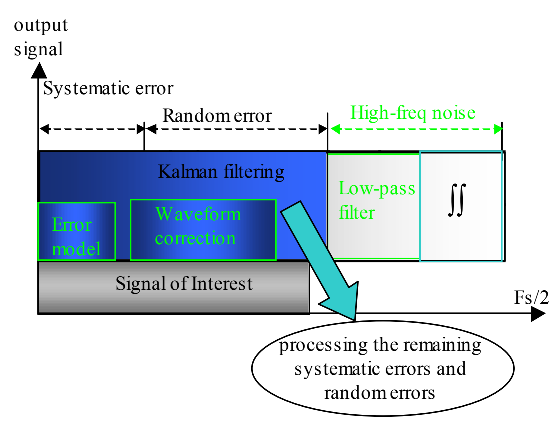


Fig. 5 Inertial system error components and corresponding error reduction

To reduce the residual errors in the inertial system, it is necessary to employ an external measurement to periodically correct the time-dependent inertial error. Kalman filter is therefore adopted in this paper to eliminate the error growth with time. In the linear position system, the system state vector **x** contains position error, velocity error and acceleration error variables:

$$\mathbf{x} = \begin{bmatrix} x_p & x_v & x_a \end{bmatrix}^T \quad (6)$$

So the system model can be stated as:

$$\mathbf{x}(k+1) = \begin{bmatrix} 1 & T & \frac{1}{2}T^2 \\ 0 & 1 & T \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_p \\ x_v \\ x_a \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ w(k) \end{bmatrix} \quad (7)$$

where: x_p —linear position error; x_v —linear velocity error; x_a —linear acceleration error. When the movement is not along a horizontal direction, the accelerometer measurement will be influenced by gravity; *T*—sampling interval; $w(k)$ — input white noise with zero mean and known covariance matrix $Q(k)$. The process noise variance $Q(k)$ can be expressed as[1]:

$$Q(k) = \sigma \begin{bmatrix} t^4/20 & t^3/8 & t^2/8 \\ t^3/8 & t^2/3 & t/2 \\ t^2/6 & t/2 & 1 \end{bmatrix} \quad (8)$$

where σ represents the standard error of the measured accelerometer data； t is the time interval of the Kalman filter.

Since the encoder measurement is used to get the strut length, the measurement model can be easily established to relate with the state vector of the inertial system. The measurement model can be expressed as:

$$\mathbf{z}(k) = \mathbf{H}(k)\mathbf{x}(k) + \mathbf{v}(k) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_p \\ x_v \\ x_a \end{bmatrix} + \begin{bmatrix} v(k) \\ 0 \\ 0 \end{bmatrix} \quad (9)$$

where, $\mathbf{z}(k)$ —position measurement from an encoder； $\mathbf{H}(k)$—an identity transition matrix; $v(k)$ —additive measurement white noise with zero mean and known covariance matrix $R(k)$. $R(k)$ depends on the accuracy of the measurements. If the measurement has an accuracy of 0.01m, then the value can be set $R_k = (0.01)^2 m^2$.

In the KF algorithm, the initial conditions (x_0 , P_0) and noise variance ($Q(0)$, $R(0)$) need to be initialised to implement the Kalman filtering recursive algorithm. The initial covariance matrix P_0 describe the uncertainty in **x** before the measurement, that is, P_{11_0} is the initial mean square error in the knowledge of position x_p , P_{22_0} is the initial mean square error in the knowledge of velocity x_v , P_{33_0} is the initial mean square error in knowledge of acceleration x_a . The $P_{ij}, (i \neq j)$ measure the corresponding cross-correlation, and are supposed to be zero. The initial covariance matrix is given in the form of

$$P_0 = \begin{bmatrix} P_{11_0} & 0 & 0 \\ 0 & P_{22_0} & 0 \\ 0 & 0 & P_{33_0} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 40 & 0 \\ 0 & 0 & 300 \end{bmatrix}$$

The $R(k)$ matrix is defined based upon the accuracy of the external measurements. When the external measurements are accurate, the variance *R* can be tuned to a small value, so the result will be closer to the measurement than one with a large *R*. In this application, the encoder has a line count 500 ppr in the PKM-Strut system, and the ratio of the belt transmission is 3:1, the ball screw pitch is 5mm, so the positional accuracy of the encoder measurement is 0.003mm. Therefore, the initial value of $R(0)$ can be set to $0.003^2 (mm^2)$. For the measured accelerometer data, the standard deviation σ is about $0.3 m/s^2$ for the PKM-Strut measurement. So the variance was initially selected as $Q(0) = (0.30)^2 m^2/s^4$. Based upon the system model, the measurement model, and the initial conditions, the Kalman filter recursive algorithm was implemented in Matlab 6.0 software.

- Position estimate

Through a suitable adjustment and tuning in the Kalman filter, the estimated position in a single run is shown in Fig.6 for a 300mm PKM-Strut movement. Through the external measurement

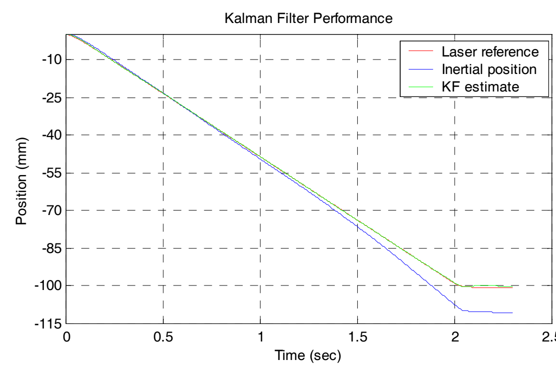


Fig.6 Inertial position from raw data, estimated position by Kalman filter and reference position by laser interferometer

fused by the Kalman filtering algorithm, the estimated STD position error was reduced from 40 to 0.15mm when raw inertial data was used, and from 16 to 0.12mm when the pre-corrected inertial data was used. With the pre-corrected inertial data used in the Kalman filtering, the positional accuracy was further improved by 20% of the accuracy of the raw inertial data used in the filter.

- Velocity estimate

In a Kalman filtering application, it is an important process to choose or tune the model noise covariance matrix Q and the measurement noise covariance matrix R. Fig.7 shows the three velocity profiles when the Q is set to a 100^2, 1^2 and 0.01^2 values. Therefore, tuning is a delicate adjustment of both the Q and R matrices. When the parameters are properly tuned, the velocity estimate from the Kalman filter integration system can contain useful dynamic information to the controller, which an encoder measurement device failed to measure.

For a large gain, due to a highly confident measurement, the covariance will diminish, which reflects the confidence supplied by that measurement. The main characteristics of the gain matrix are determined by the ratio of Q/R. A large Q will imply an inaccurate inertial system model. During the prediction stage the uncertainty in the inertial data will grow according to the amount of noise injected. When an external fix does occur, there is a greater possibility the inertial data will be corrected using the first available fix irrespective of the accuracy of this fix. A small R value will imply accurate external measurements and result in the inertial data closely following this external measurement fix. If the external measurements have high uncertainty and hence are noisy, then the corrected inertial data will also be noisy.

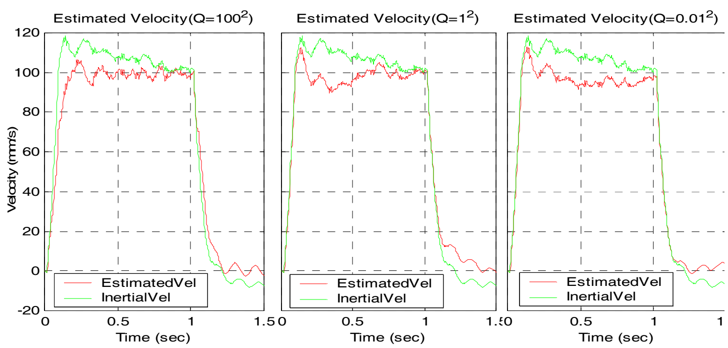


Fig.7 Velocity estimate determined by Kalman filter tuning

V. EVALUATION AND CONCLUSION

To effectively suppress inertial error growth, an external measurement has to be used to periodically update the inertial error. The Kalman filtering was therefore designed in this paper to update the inertial error through the integration of the inertial and encoder measurements for the linear movement. As a result, the Inertial/Encoder integration system corrected most of the inertial errors and improved the inertial positioning accuracy by 99% for the measurement. If the pre-corrected inertial data is used in the Kalman filter, the positional accuracy was improved to 0.12mm, a further 20% improvement of the accuracy for the 300mm movement was achieved.

Obviously, the proposed low-cost inertial positioning system at present cannot be expected to achieve as high dynamic accuracy as the Variax machine where expensive laser interferometers are used for each strut length measurement. But considering the achievable dynamic positional accuracy from the accelerometer-based measurement system and the advantage of being small size, low-cost, and self-contained, the inertial dynamic measurement system is a possible solution for the parallel kinematic machine to improve its dynamic positional accuracy.

ACKNOWLEDGMENT

The project is sponsored by the Scientific Research Foundation of Guangdong Provincial Science and Technology Department (Grant No.2006A10405005).

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