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A SERVO SYSTEM WITH REDUNDANT ACTUATORS

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This paper presents a control law of multiple actuation servo systems. Multiple actuation systems have an ability to solve some difficult engineering problems; Coulomb friction, backlash, and disturbance. This fact is shown by basic experiments as well as theoretical analysis. The proposed control strategy remarkably improves the performance comparing with conventional single actuation systems.

Keyword: Redundant Actuator, Multiple Actuation, Coulomb Friction, Sensor Dead-zone, Backlash

1 Introduction

Though control problems on servo systems have been well studied, there exist still many engineering problems; Coulomb friction, backlash, sensor dead-zone must be solved to realize servo system of high performance. The general method to realize high performance is to improve each element of constituting the servo system. But, as for this method, both a problem on precision technology and increase of production cost are never averted.

We propose a method that achieves high performance by using multiple general servo units together, by which the performance of the servo systems is remarkably improved comparing with single actuation systems against the exisitence of nonlinear factors. Though this method increases the energy cost in steady state, but it can achieve high precision easily. While this control strategy is very simple, we can theoretically show that this system has high precision and high robustness in spite of heavy gear backlash, coulomb friction and sensor dead-zone.

2 A Problem on Servo System

A simple description of servo systems is as follows.

$$\frac{d}{dt}x = \begin{bmatrix} 0 & 1 \\ 0 & -d/m \end{bmatrix} x + \begin{bmatrix} 0 \\ b/m \end{bmatrix} u \quad (1)$$

$$y = \begin{bmatrix} c & 0 \end{bmatrix} x \quad (2)$$

Where the state x is two dimensional vector that consists of position and velocity; the coefficients m, d, b and c are mass, viscosity friction coefficient, the input torque constant, and the output gain respectively. We derive the control input u as a feedback of state to let the output y coincide with the reference value.

Control input u is generally expressed as PID form of the output y when we use observer as a stale estimator. Usually, we set the input torque coefficient b and the output gain c be constant to treat the system as a linear system. But, b and c are nonlinear functions by the effects of coulomb friction, backlash of actuation system, sensor dead-zone and sampling error of AD conversion. These nonlinear functions have saturation and hysterisis, thus it is difficult to describe them precisely.

The nonlinear characteristics don't give serious influence in large motion, but gives damages in micro motion. Namely this nonlinear characteristics sometimes cause minute vibration and ill convergence when the servo system approaches to the reference value.

3 An Advantage of Multiple Actuation

In the sequel, let us theoretically consider the following simple system to explain the benefits of multiple actuation systems. The target servo system is described by the same equation as Eq.(1) and Eq.(2) but with two control inputs.

$$\frac{d}{dt}x = \begin{bmatrix} 0 & 1 \\ 0 & -\frac{d}{m} \end{bmatrix} x + \begin{bmatrix} 0 \\ \frac{b_1}{m} \end{bmatrix} u_1 + \begin{bmatrix} 0 \\ \frac{b_2}{m} \end{bmatrix} u_2 \quad (3)$$

$$y = \begin{bmatrix} c & 0 \end{bmatrix} x \quad (4)$$

Where u_1 and u_2 correspond to the two actuator torques. We assume the all coefficient are constant by charging the all nonlinear characteristics to the control portion. We adopt proper position feedback controls for these two actuators,

$$u_1 = f_1(y^* - y) \quad (5)$$

$$u_2 = f_2(y^* - y) \quad (6)$$

If $u_2 = 0$ and f_1 is a constant coefficient, the control input u_1 may derive the servo system to the reference position y^*. Howevere, the torque function $f_1(\cdot)$ must be nonlinear function by the effect of backlash, coulomb friction and sensor dead-zone of the original system as shown in Fig.1. $f(y^*)$ is a function defined on angle space of the servo system, and it takes value on torque space. In practical sense, this function means the correspondense between the generating torque and the system angle y. The dead-zone character comes from the back-lash of the servo mechanism, coulomb friction of servo mechanism, coulomb friction inside actuators and sensor dead-zones.

Due to this nonlinearity, the closed loop system does not converge to the exact value y^*, but only approach to the neighbourhood of y^*. Since the convergence depends on various practical factors, the converged point is not definite and it can not be identified.

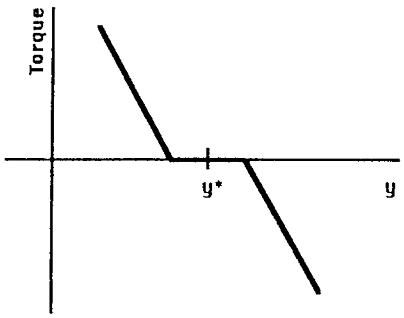

Fig.1 Property of torque function

Let us consider multiple actuation case. We use both of u_1 and u_2 by giving the references ${y^*}_1$ and ${y^*}_2$. If ${y^*}_1$ is not equal to ${y^*}_2$, some conflict may occur in process of convergence. But if the difference is enough small, the system converges into the neighbourhood of y_1 or y_2 without any confliction. Let us consider the following case.

$$u_1 = f(y^* + \epsilon - y) \quad (7)$$
$$u_2 = f(y^* - \epsilon - y) \quad (8)$$

The sum of two torques f_1 and f_2 is described as in Fig.2. As shown in Fig.2, the dead zone decreases down to the intersection of f_1 and f_2. If we choose ϵ properly, the dead zone may disappear at all. It means the sum of the torque functions become a torque function which has no dead-zone and whose zero-cross point is between $[y^* - \epsilon, y^* + \epsilon]$. If the dead-zone disappears completely, the zero-cross point is unique, and the servo system converges this definite point.

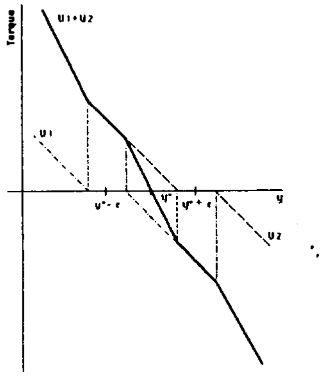

Fig.2 Property of $f_1 + f_2$

By this way, we can make the servo system converge to a definite point even if there exists unknown dead-zone. Namely we can cancel the back-lash of main mechanism and compensate the effect of coulomb friction inside the actuators. However the converged point can not be identified, we can only say it exists just between $[y^* - \epsilon, y^* + \epsilon]$.

4 Control Strategy

As stated before, the converged point by the above strategy may not coincide with the target point y^*. Let us try to adjust this converged point to the target point as near as possible. Since there exits sensor dead zone, we cannot know the exact angle of the servo system.

We represent the dynamical system by the following mathematics model with n independent actuators.

$$\dot{x} = Ax + b\sum_{i=1}^{n} \beta_i(u_i) \quad (9)$$
$$y_o = c_o x \quad (10)$$
$$y_i = c_i(x) \quad i = 1, \cdots\cdots, n \quad (11)$$

Where y_o is the true output of the system, which should be converged to the given target. $y_i, i = 1, \cdots, n$ are observations of each actuation. $\beta_i(\cdot)$ is the function that describes each inputs nonlinearity.

We assume the servo system can be composed by only using any one of the actuators. Let us describe the feedback strategy as the following maping.

$$u_i = f_i(y^*, y_i) \quad (12)$$

Where f_i includes the dynamics of the controller. The each control input is calculated by using its own output and the common reference value. Each actuator tries to let the output y_o converge to the reference value y^*, but all of the actuators cannot success the exact convergence due to the nonlinear effect around y^*. Let us an artificial disturbance to each reference value.

$$u_i = f_i(y^* + \epsilon_i, y_i) \quad (13)$$

By this disturbances, each actuator tries to let the output to each different reference value. Though the actuators work contrary around the real reference value y^*, the output converges to an unique point by the mechanical constraint. However the converged point may not be the exact reference point. This offset can be compensated by the following way.

$$u_i = f_i(y^* + \epsilon_i + \delta, y_i) \quad (14)$$

We add a common bias δ to each reference value. By adjusting this bias δ, we can lead the convergence point to the exact reference point. We can adjust the bias δ by a kind of integral feedback.

$$\dot{\delta} = \alpha(y^* - y_o) \quad (15)$$

Where α is an enough small positive constant. Let us theoretically consider the control law Eq.(14) and Eq.(15) to prove its validity. Let x^* be the equilibrium state corresponding to the reference value y^*. The equilibrium satisfies $Ax^* = 0$ because x^* is an equilibrium at $u = 0$ in Eq.(9). An optimal regulator of Eq.(9) is described as follows.

$$u = -\frac{1}{r} b^T P(x - x^*) \quad (16)$$

Where P is the positive definite symetric matrix of satisfying the following Riccati equation with an appropriate positive constant r and a positive definite matrix Q.

$$A^TP + PA - \frac{1}{r}Pbb^TP + Q = 0 \qquad (17)$$

Each actuator estimates the state from its own output y_i by using its own observer.

$$\begin{aligned} \dot{x} &= Ax + b_iu_i \\ y_i &= c_ix \end{aligned} \qquad (18)$$

Naturally the estimated value contains error $r_i(x, x^*)$ which is caused by transient effect and by nonlinear effect. Thus, the control law is represented as follows.

$$\begin{aligned} u_i &= f_i(y^*, y_i) \\ &= \frac{1}{n}(-\frac{1}{r}b^TP(x - x^*) + r_i(x, x^*)) \end{aligned} \qquad (19)$$

Let us consider the following Lyapunov function to evaluate the control law.

$$L(x) = (x - x^*)^TP(x - x^*) \qquad (20)$$

From $Ax^* = 0$, the derivative of this Lyapunov function is described as follows.

$$\begin{aligned} \frac{d}{dx}L(x) &= (x - x^*)^T(A^TP + PA)(x - x^*) \\ &+ 2(x - x^*)^TPb\sum_{i=1}^{n}\beta_i(f_i(y^*, y_i)) \end{aligned} \qquad (21)$$

We can rewrite Eq.(21) as Eq.(22).

$$\begin{aligned} \frac{d}{dx}L(x) &= -(x - x^*)^TQ(x - x^*) \\ &+ 2(x - x^*)^TPb[\frac{1}{2r}b^TP(x - x^*) \\ &+ \sum_{i=1}^{n}\beta_i(f_i(y^*, y_i))] \end{aligned} \qquad (22)$$

We let $r_i(x, x^*)$ be the accumulated error of $r_i(x, x^*)$ and the nonlinear term included in $\beta_i(\cdot)$.

Finally, Eq.(21) is expressed as follows.

$$\begin{aligned} \frac{d}{dx}L(x) &= -(x - x^*)^TQ(x - x^*) \\ &- (x - x^*)^TPb\frac{1}{r}b^TP(x - x^*) \\ &+ 2(x - x^*)Pb \cdot \frac{1}{n}\sum_{i=1}^{n}\hat{r}_i(x, x^*) \end{aligned} \qquad (23)$$

5 Experiment

Each experiment was done in angle range $[0^\circ, 90^\circ]$ and the initial angles were fixed at $0^\circ, 45^\circ$ or 90°. The target angles were distributed at every 2° in angle range $[0^\circ, 20^\circ]$. Each positioning was repeated 30 times and every data were recorded. After many trials, we determine the each artificial disturbance ϵ at each reference angle, which gives the minimum covariance of the error. The bias δ is given as the difference between the reference and the average at the selected ϵ.

The first experiment is about conventional servo system. We have adopted PI controller with the best tuned parameters, the actuator angle converges almost precise value as given reference. However the output angles of the whole system measured by the encorder system as shown in Fig.3. The errors distribute in wide range around the target angle. This is because main gear wheel has a large backlash.

Next we have used two actuators simultaneously. Let us feed the target angle $y^* + \epsilon$ and $y^* - \epsilon$ to the two actuators respectively, where the small parameter ϵ is tuned to the best value which can cancel the back-lash of main gear wheel as possible. The results are shown in Fig.4. This result is remarkably improved comparing with the single actuator case. But, due to sensor dead zone, the output include non-negligible error at several given reference angle.

The next experiment has been done in the same situation as the above experiment. But the reference command fed to the servo systems are $y^* + \epsilon + \delta$ and $y^* - \epsilon + \delta$ respectively as explained above. The result is shown in Fig.5. It keeps small error distribution all over the reference values.

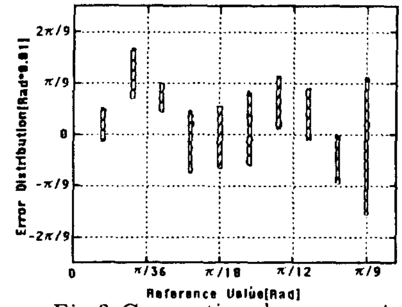

Fig.3 Conventional servo system

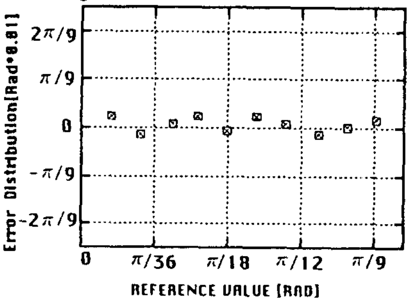

Fig.4 Multi-Actuation Servo System

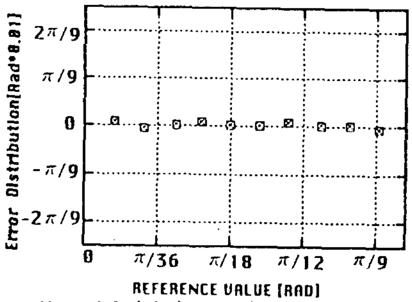

Fig.5 Multi-Actuation Servo System

6 Interporation of ϵ and δ

The value ϵ and δ strictly depend on the reference value. Thus, we have to determine each ϵ and δ of corresponding to each reference value by off-line manner in advance. It is almost impossible to prepare every ϵ and δ for every arbitrarily given reference.

Therefore, we have to introduce a kind of interporation method to overcome this problem. The typical tools for interpolation are "neural network" and "spline function". We have tried to use these two tools for the interpolation. At first, we had determined the optimal parameters ϵ and δ every 0.5^o between $[5^o, 90^o]$.

We used the above 170 data as the teaching data to the three layer network. We adopt conventional backpropagation algorithm for the learning. The learning was almost finished after 35000 iterations. The spline function used here is a set of three dimensional polynomial functions. These functions are continuously connected at 60 points of the above 170 nominal points. Fig.6 shows the total spline function between $[5^o, 90^o]$.

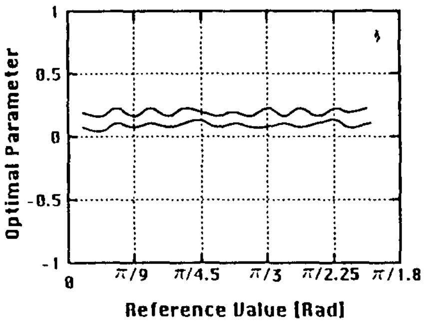

Fig.6 Total Spline Function

The experiment was done by the following procedure,

(1) 1000 reference angles are selected randomly between $[5^o, 90^o]$.

(2) For the each above reference angles, the each positioning is done by using the parameter ϵ and δ derived through the neural network or the spline function interporation.

The error distributions are shown in Fig.7-(a) and Fig 7-(b). The covariances are 0.0204 in neural network approach and 0.0087 in spline approach. We know that the spline function approach is much better than the neural network approach. The reason may be that neural networks are not suited to treat such analog data.

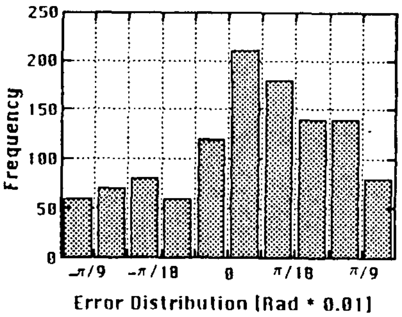

Fig.7-(a) Error distribution(NN approach)

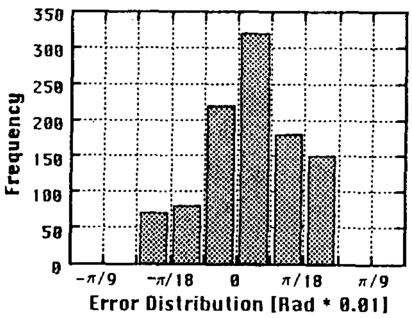

Fig.7-(b) Error distribution(spline approach)

7 Conclusion

In this paper we have reported the outline of a new control architecture of systems which have redundant actuators. Even each actuator has not enough precision, the precision of the total servo is remakably improved to high precision. And the servo system has also high robustness by the effect of redundant actuation. The point should be underlined is the parameters ϵ and δ for the commands of the servo system are able to determined by automatic learning. Because the data can be gotten by only repeated positioning experiments and the spline function or the neural network can be also gotten systematically.

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