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A friction estimation approach to fault detection in electromechanical systems

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Abstract: This paper presents a sensor fusion approach, using an Extended Kalman filter, in order to estimate the friction coefficient inside an electromechanical system. This method has the main advantage of merging the information arising from acceleration and motor current into a single variable. This new signal permits to improve the performance of a fault detection algorithm. An application showing the advantages of the proposed approach is shown; the electromechanical system chosen for the tests is an automatic access gate.

Keywords: Sensor data fusion, fault detection, friction estimation, Extended Kalman filter

1. INTRODUCTION

The research field related to the fault-detection is very wide since in every system a failure can happens and knowing the type of fault can increase the safety. An important requirement for fault detection algorithms is the ability of identify the faults in most of the possible conditions. In order to achieve this goal, the best knowledge of what is happening inside the system is needed. Due to this, the typical solution is to place as many sensors as possible for collecting more data, and consequentially more informations. However, this way leads to increase the complexity of the algorithms making the fault detection process slow. This fact assumes a significant importance when the time required for identify the fault is crucial. Some suitable examples for this case can be found in robotics, in particular in the human-robot interaction themes (De Luca and Mattone [2005], Haddadin et al. [2008], Filippini et al. [2008]). With the purpose of increasing the best available information gotten by the signals, and thus reducing the quantity of data with which the fault detection algorithm has to work, a sensor data fusion approach is typically used (Luo and Kay [1990], Luo et al. [2002], Vershinin [2002]). The idea is to combine the information provided from multiple sensors to get a new data with a more suitable information content. A typical example of application where this approach is widely used is the orientation estimation of the objects (Comotti et al. [2014]).

The work presented in this paper approaches the problem of the fault detection. In particular the impact detection issue is addressed, using a real application case based on an automatic access gate. This system can be considered as a generic speed-controlled electromechanical system: it is composed by an electric motor which moves a load through a mechanical transmission. About these type of systems taken into account, in literature exists different methods which affords to detect faults on the basis of the data collected from the measurements. In particular there exists a branch of approach which use the data from the currents of the motor (Zarei [2012], Romeral et al. [2010]), other which use vibrational measurements (Cristalli et al. [2006]) and others which detect the fault using a thermal camera (Nandi et al. [2005]). More in deep, the current has a good information content on the overall system about the arising of a fault thanks to the control system which tends to compensate the unexpected behavior. However, for the same reason, it is affected by a time delay depending on the performance of the controller. This fact has a great relevance in particular when the fault has to be detected in the minimum time as possible; for example in any type of collisions avoidance or in an electromechanical actuator included in safety system, the reaction time is of primary importance. This type of method is called *Electrical Signature Analysis (ESA - El Hachemi Benbouzid [2000])*.

Along these lines, this work proposes an integration of the measurement of the motor current with the data from an accelerometer, in order to obtain a new data with an higher information content. In detail, it is presented a sensor data fusion method between the measurement of motor current, the speed of the system and its acceleration with the aim of estimate the viscous friction coefficient of the mechanical system. As it is shown in the model section, the concept idea is to represent the fault as a variation of friction of the system. This approach, beyond giving an intuitive physical meaning to the fault, as shown in the application case section, it improves the performance of the fault detection algorithms.
These concepts will be presented using a real application case like the problem of impact detection in an automatic access gate.

The paper is organized as follow: in section II the problem is introduced, describing the context and the model taken

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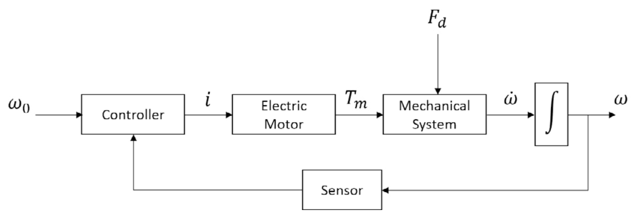

Fig. 1. Block diagram of a speed controlled electromechanical system

into account. Then, in section III the sensor data fusion algorithm, called *FEEKF* (acronym of *Friction Estimation Extended Kalman Filter*) is explained. In section IV the previous algorithm is applied in a real case, in order to show its performance and its widely applicability in different contest of fault. In section V the results achieved using the parameter estimated by the *FEEKF* are compared to the ones achieved with the same fault detection algorithm but with raw signals as inputs. Then in section VI the paper comes to an end speaking about possible advantages and drawback of the proposed system.

2. PROBLEM STATEMENT

In order to introduce the proposed method consider, as a paradigmatic example, a speed controlled electromechanical actuator with an external force acting on it, as shown in figure 1. This force represents the physical effect of an event affecting the system, due to an unexpected phenomenon like a collision or a general fault.

The physical model of the system considered is shown in figure 2. A motor, through a mechanical transmission, moves a mass where is present a dissipative force, represented as viscous friction. In real situations the mass J represents all the inertia of the system: it includes the motor inertia J_m, the inertia of the transmission J_t and the inertia of the loads J_l. The torque T_d is the effect of the unexpected event. For the aims of this work some assumptions on the model has been made, in particular:

- the mechanical transmission is considered rigid;
- the model of the electric motor and the power losses due to the deformation of the parts of the system are not considered;

The motor torque T_m is estimated form the current through the follow relation:

$$T_m = K_t \cdot i \tag{1}$$

where i is the current circulating in the motor and K_t the related torque constant.

The behavior of the overall system (visible in figure 3) is described from a dynamic equilibrium:

$$\frac{T_m(t)}{\tau} - c_f \cdot \omega(t) - T_d(t) = J\dot{\omega}(t) \tag{2}$$

where:

- c_f is the viscous friction coefficient;
- ω, $\dot{\omega}$: are respectively the angular speed and the angular acceleration of the mechanical system;

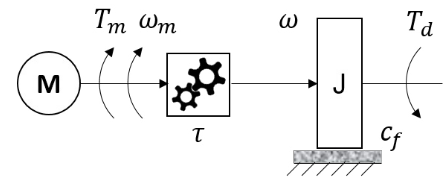

Fig. 2. Physical model of the system

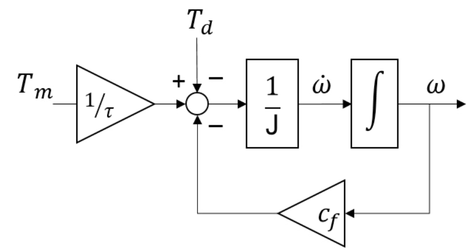

Fig. 3. Block diagram of the system

- τ is the reduction ratio, defined as the ratio between the output and the input speed of the transmission ($\tau = \omega/\omega_m$);
- J is the moment of inertia of the overall system ($J = \frac{J_m}{\tau^2} + J_t + J_l$)

The concept presented in this work describes the event T_d as a variation of the friction coefficient of the system:

$$T_d(t) = c_d \cdot \omega(t). \tag{3}$$

Thus, the final model equation becomes:

$$\frac{T_m(t)}{\tau} - c \cdot \omega(t) = J \cdot \dot{\omega}(t) \tag{4}$$

where $c = c_f + c_d$ is the global viscosity friction coefficient of the system, the parameter to be estimated. To be noted that, the variable estimated is composed by two components; in this framework, the unexpected external event can be modeled as a sudden change in the viscosity friction coefficient. This parameter, as shown in the next section, is estimated using an Extended Kalman filter. As the application case will show, this information about the system suffers a crucial change in presence of failure. This helps the algorithm of fault detection, and can highly improve its performance without introducing complexity in it.

3. FRICTION ESTIMATION EXTENDED KALMAN FILTER (FEEKF)

Starting from the last model equation (4), the goal is to estimate the friction coefficient c of the system, given the measurement of the motor torque (T_m), the speed (ω) and its acceleration ($\dot{\omega}$). The torque is an estimation from the measurement of the current of the motor, as described in (1). The motor speed ω can be measured using an encoder or a similar sensor. The data of angular acceleration can be computed from an Inertial Measurement Unit (*IMU*); depending on where it is placed, there exists a constant relationship between the linear acceleration measured and the angular acceleration of the motor $\dot{\omega}$ (for example, in the application case reported in section 4 it is the reduction ratio of the transmission).

Since the model is nonlinear, in order to solve the estimation problem, the Extended version of the Kalman filter must be used. As reported in Grewal and Andrews [2011], the *EKF* consists in applying linearization techniques about the estimated trajectory, to get simple approximation of the system and then compute the Kalman filter gain respect these points. The principal drawback of the *EKF* is the loss of optimality guaranteed by the linear Kalman filter.

Thereby to formulate the Extended Kalman filter problem, there are three main steps to follow:

(1) basing on the model equation, define the state space model of the system;
(2) linearize the system;
(3) define the noise covariance matrix Q and R.

About the first step, given the measurement of the motor torque, the speed and the acceleration, the state variables of the system are defined as:

$$x_1 = c$$
$$x_2 = \dot{\omega}$$
$$x_3 = \omega$$

while the motor torque T_m/τ is defined as the input u of the system. Hence, the state space model in discrete time is:

$$\begin{cases} x_1(k+1) & = x_1(k) + w_1(k) \\ x_2(k+1) & = \frac{u(k)-x_1(k)x_3(k)}{J} + w_2(k) \\ x_3(k+1) & = x_3(k) + T_s x_2(k) + w_3(k) \\ z_1(k) & = x_2(k) + v_1(k) \\ z_2(k) & = x_3(k) + v_2(k) \end{cases} \tag{5}$$

where w_n represents the uncorrelated noise of the plant, while v_m the uncorrelated noise in the measurement. T_s is the sampling time.

The second step consists in linearize our model; starting from the classic state space description of nonlinear system:

$$\begin{cases} x(k+1) & = f(x(k+1), u(k)) \\ z(k) & = h(x(k), u(k)) \end{cases}$$

the system is linearized in the following manner:

$$\delta F = \frac{\delta f(x,u)}{\delta x} = \begin{bmatrix} 1 & 0 & 0 \\ -\frac{x_3}{J} & 0 & -\frac{x_1}{J} \\ 0 & T_s & 1 \end{bmatrix} \tag{6}$$

$$\delta H = \frac{\delta h(x,u)}{\delta u} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{7}$$

Finally, to complete the formulation the covariance matrix of the model is defined as:

$$Q = \begin{bmatrix} \sigma^2_{w_1} & 0 & 0 \\ 0 & \sigma^2_{w_2} & 0 \\ 0 & 0 & \sigma^2_{w_3} \end{bmatrix}, \ R = \begin{bmatrix} \sigma^2_{v_1} & 0 \\ 0 & \sigma^2_{v_2} \end{bmatrix} \tag{8}$$

Fig. 4. Image of the gate used for the tests

where Q represent the covariance matrix related to the plant noise while R is linked to the measurement noise. In the application case presented, the values for these matrices are assigned using a trial and error method.

4. APPLICATION CASE

In this section a particular application case will be presented, highlighting the potential of the sensor fusion solution proposed in this work.

4.1 Problem Description

The electromechanical system used to test the algorithm is an automatic access gate, showed in figure 4. The goal is to detect, in the minimum time, an impact of the gate against a person, a car or any other object. Obviously, from a safety point of view, the impact with a human is the most significant to detect.
This lead to an examination of the different type of impact:

- *Stiff*: it relates to collisions between a gate and rigid objects (*e.g.* human cranium or other bones);
- *Soft*: this type of impact refers to collisions among the gate and soft items (*e.g.* parts of the human body covered by muscle or fat). Another crucial condition, modeled as soft impact, happens when a person remain stuck between the gate and the barrier at the end of the track, being pressed by the gate.

Since the system now is completely described is easy to deduce that the *stiff impact* will produce an higher deceleration compared to the *soft* one.

On the other side, a *soft impact* will be more visible on the torque signal, due to the slow increase of the force needed to overcome the obstacle. Due to these remarks, the sensor fusion algorithm described in section 2 perfectly matches the requirements, promising better performance in terms of impact detection in all the conditions.

4.2 Experimental setup

The mechanical structure of the gate consists of four principal component:

- motor: typically a synchronous brushless motor, with the speed of the rotor calculated by the resolver;

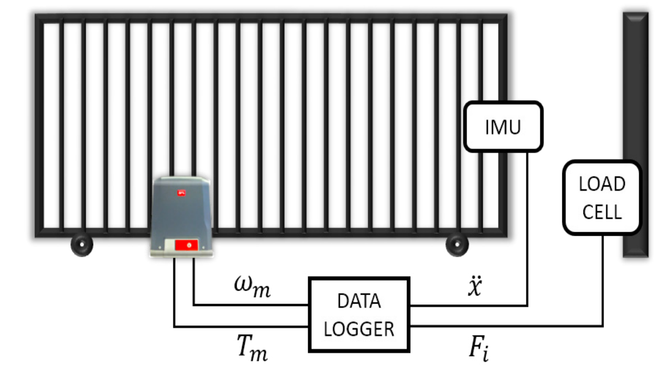

Fig. 5. Schematic of the experimental layout. The position of the IMU and of the load cell reflects the real location during the tests.

- transmission: reduce the rotational speed, increasing the torque produced in output;
- rack: transform the motion from rotational to linear;
- moving mass: this is effectively the gate, which moves forward and backward, opening and closing the access.

The Extended Kalman Filter described in section 2, requires three measurements from the system:

(1) acceleration: using an accelerometer placed on the moving part of the gate the acceleration is easily measured. Since the derivative of the angular speed is needed, using the following equation the linear acceleration is transformed into a rotational one:

$$\dot{\omega} = \frac{a_l}{\tau} \tag{9}$$

where τ is the gear ratio and a_l the longitudinal acceleration;

(2) torque: in this case, the torque is estimated directly from the motor current:

$$T(t) = K_t \cdot i_m(t) \tag{10}$$

where i_m is the current in the motor and K_t is the coefficient which relate the current to the torque;

(3) angular velocity: this variable is acquired through a resolver connected to the motor.

In addition to these data and only for validation purpose, the force of the impact is acquired using a load cell. This sensor permits to understand when the collision begins and, as a consequence, an evaluation of the time required by the algorithm to identify the impact. The load cell chosen has a stiffness of $500N/mm$ which approximates the rigidity of a human cranium.
The experimental layout is described in figure 5.
The two types of collision defined in 4.1 are recreated in this way:

- *Stiff*: using the load cell previously described;
- *Soft*: placing a rubber bumper in front of the gate, which absorbs a part of the impact force.

All this data are acquired using a dedicated electronics which runs the algorithm in real-time. The embedded system permits to stop the gate in case of detection of the impact.

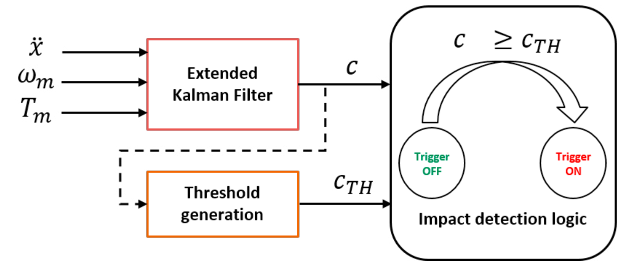

Fig. 6. The structure of the algorithm is briefly resumed in the figure. The torque, the angular speed and the acceleration permits to estimate the friction coefficient. Then this parameter is used for the creation of the *signature* and the identification of the impact.

4.3 Impact detection algorithm

The algorithm for the identification of the impact (resumed in figure 6) can be divided into two parts. The first is the *FEEKF* algorithm, needed for the generation of the friction coefficient, used in the detection algorithm. The second part effectively describes how the collision is identified. Since the behavior of the system is deterministic the impact can be detected comparing the actual value of the friction coefficient with a threshold curve which represents the normal behavior of the system without collision. This threshold curve is defined as the *signature* of the gate. In the following, the *threshold* generation process and the impact detection logic are presented.

Signature creation and update In this phase a number ($>$ 10) of closing operation without impact has been carried out, estimating for each operation a friction coefficient curve. The threshold is then created taking the mean of these curves and increasing it by a safe-factor, in this case the standard deviation. Each time the gate completes a closing operation without impact the *signature* is updated with the new values; in this way the behavior of the gate is updated, matching the changes in the environment (weather, aging of the components etc.).

Impact detection Once the reference behavior is created the impact can be detected simply identifying when the friction coefficient exceeds the *signature*, as visible in figure 7.

5. RESULTS

In this section, the results achieved on the real system described in section 4 are shown. The performance of the sensor-fusion algorithm are then compared with two other methods.

The benchmark used to test the performance consists in a closing operation at the maximum speed reachable by the gate. In particular the reliability of the algorithm is tested in the two different type of impact described in section 4.1.

In order to compare the performance, two other type of algorithm have been developed. They have the same structure of the one shown in figure 6, with the main difference that there's no sensor fusion and the *signature* is generated on the basis of a single information:

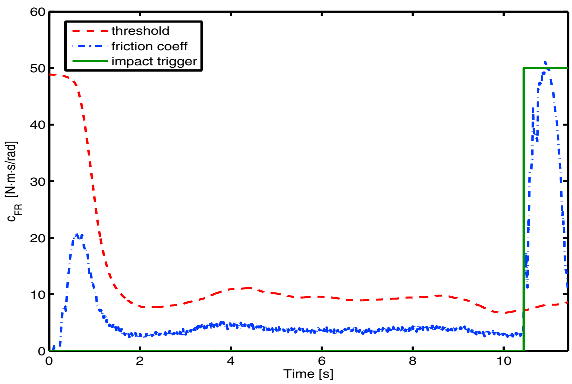

Fig. 7. The figure illustrates how the algorithm identifies the impact. In red (dashed line) is visible the *signature* created during the setting up of the system. In blue (dashed-dotted line) there is the friction coefficient estimated during a closing operation. In green (solid line) is visible the trigger which identifies the impact. It is clear that when the blue line exceeds the red one the impact is detected.

- Torque for the *motor-side* algorithm;
- Longitudinal acceleration for the *pure inertial* algorithm.

More in deep, a number of closing operations without impact are done. During these operations two signatures, one based on the accelerometer and the other on the torque, are created. The creation of these signatures is made taking for each instant, the mean of the signals and increasing the value by the variance. At this point, during a normal operation, the raw signals read are compared to the respective signature. If the measurement overcome the signature a trigger is activated.

The gate used for the tests has a weight of 620 Kg and a maximum speed of 12 meters per minute.

5.1 Stiff impact

The trigger activations for the stiff impact which, recalling the concept, represents a collision with a rigid object, are shown in figure 8 and the performance of the algorithms are summarized in the table 1.

In case of stiff impact an high level of acceleration is detected and, as a consequence, the algorithm which uses only the accelerometer signals is the fastest to detect the collision. The sensor fusion algorithm takes the advantages from the accelerometer signals and identifies the impact very quickly, while the *motor-side* method detects the collision only when the control increases the current in order to overcome the obstacle. As a result, the best performance are achieved by the *FEEKF* and the *pure inertia* algorithm.

5.2 Soft impact

A soft impact happens when the stiffness of the object against whom the gate hits is low. In the application presented, this type of impact is recreated placing a rubber bumper on the moving part of the gate. The performance

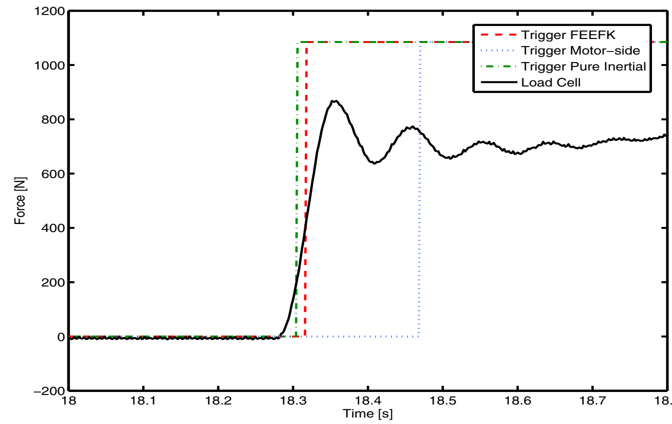

Fig. 8. Trigger of activation of the algorithms during a stiff impact at maximum speed. The red dashed line is the *FEEKF*, the green dashed-dotted line is the *pure inertial* algorithm and the blue dotted line is the *motor-side* algorithm. The black continuous line is the force of the impact measured by the load cell.

Algorithm type	Activation time [ms]	
	Mean	Std deviation
FEEKF	34	3
Pure inertia	22	3
Motor-side	186	20

Table 1. Performance of the algorithms in case of stiff impact. The mean and the std deviation are computed using 30 impact tests.

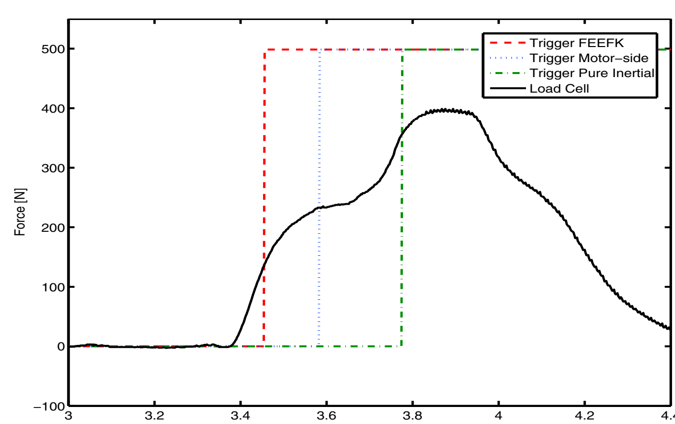

Fig. 9. Trigger of activation of the algorithms during a soft impact at maximum speed. The red dashed line is the *FEEKF*, the green dashed-dotted line is the *pure inertial* algorithm and the blue dotted line is the *motor-side* algorithm. The black continuous line is the force of the impact measured by the load cell.

are summarized in table 2, while in figure 9 the activations of the triggers, compared to the force of the impact, are shown.

The effect of the bumper is visible in figure 9; in fact the slope of the force is not continuous, it has two steps.The first is related to the force absorbed by the bumper, while the second starts when the bumper has ended its work.

The first algorithm to identify the impact is the *FEEKF*, which is able to perfectly mix the information from the accelerometer and the torque; the worst performance is achieved by the *pure inertia* algorithm; in this type of impact the amount of acceleration measured is very low.

Algorithm type	Activation time [ms]	
	Mean	Std deviation
FEEKF	66	15
Pure inertia	386	6
Motor-side	193	8

Table 2. Performance of the algorithms in case of soft impact. The mean and the std deviation are computed using 30 impact tests.

5.3 Consideration

The overall performance is increased by the introduction of the *FEEKF*. In fact, keeping the same fault detection algorithm, the sensor fusion permits to highly increase the efficiency of the detection, in terms of time required and robustness to different type of impact.

6. CONCLUSIONS

In this work a sensor fusion method was presented with the aim of providing a new useful information data with which it is possible to detect a fault in a electromechanical system. The advantage of this approach, beyond giving a physical meaning to the variable estimated, is that it condenses in only one signal the information content of three difference measurements. In this way it allows simplifying the algorithm of fault detection which have to elaborate the data coming only from one source, and furthermore, it improves its performance. These points have been proved in the application case proposed, where for safety reason the detection algorithm must be able to detect the fault related to the collision in a minimum time as possible and in different conditions of impact. Now that the algorithm has been tested on an access gate, the next step will be to test it on another electromechanical system, in order to evaluate the performance in other conditions and for other purposes.

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