Toward State-Unsaturation Guaranteed Fault Detection Method in Visual Servoing of Soft Robot Manipulators

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Abstract—This paper puts forward a novel sensor-less fault detection method with only task errors feedback and applies it to visual servoing tasks of soft robot manipulators. The method is developed by introducing a suitably designed endogenous accessory signal (EAS). On the one hand, EAS transforms the change of jacobian matrix led by faults into the change of task errors, which enables the fault to be directly measured and detected; on the other hand, EAS adjusts the state trajectories according to the distance between states and their boundaries, so that state saturation is avoided. To enhance the robustness of the method, we introduce an artificial potential field that keeps the states from the undesired hyperplanes that lead to the loss of effectiveness of the method. Due to the uncalibrated feature point, its coordinates used in control laws and artificial potential filed are unknown. An adaptive algorithm is developed to guarantee the stability of the system and the convergence of the image errors. Experiments are conducted to validate the performance of the proposed method in both healthy and faulty systems.

I. INTRODUCTION

Inherently being compliant with the natural tissues of human and living organisms, soft robot instruments are widely used in applications demanding safe interaction within a dynamic environment [1], [2]. This has motivated the development of soft robot manipulators for surgical interventions, which can also be disposable to ensure zero risk of endoscopy-related infection transmission [3]. To ensure the security of patients, the reliability of the soft robot manipulator is critical. Designing fault detection and identification (FDI) algorithms and fault-tolerant control strategies are one of the most cost-efficient ways to improve reliability.

The fault detection methods for manipulators are classified into four categories: data-driven methods, observer-based methods, hybrid methods, and active methods. In terms of data-driven method [3], [4], it proposes a framework to learn the characteristics of the normal mode and faulty modes, and distinguishes them without prior knowledge of the structural parameters of robots [3]. However, it is unsuitable for disposable surgical soft robot manipulators because its accuracy heavily depends on the activation function and termination condition used during training, which must be selected through trials until acceptable results are achieved [5]. Without trials, observer-based method [6] detects faults by synthesizing varied sensed information and reconfiguring system states. Whereas considering the limitation of cost, we cannot equip low-cost and disposable surgical soft robot manipulators [7] with costly sensors, for example, optical encoders and fiber optics [8], and usually images captured by endoscope are the only feedback. Hybrid method [9] is the combination of the two methods, and therefore, has both of their drawbacks.

Active method is an accurate method to detect faults utilizing only task errors feedback. Initialized in [10], it distinguishes the normal mode from faulty modes by injecting auxiliary signals into the dynamic process, for example, servoing and tracking. However, most of the active methods [11] are invasive, which means injected auxiliary signals lead to negative influences on the real-time performance of the system, for instance, disturbance and instability, [12] first proposes an active fault detection method that transforms exogenous auxiliary signals into endogenous ones, then avoiding the disadvantages caused by auxiliary signals. However, it also generates the problem: the states are easy to be saturated when using the method. To solve this problem, we propose a novel active fault detection method based on suitably designed endogenous accessory signal (EAS) that could guarantee the unsaturation of states and detect faults for sensor-less soft robot manipulators with only image feedback simultaneously. A specific example of the method is presented to detect frozen motor faults in visual servoing tasks of soft robot manipulators. Frozen motor faults are the faults that some motors are unable to respond to the control signals and have constant outputs on account of mechanical failures. As a result, the lengths of cables driven by motors are unable to change until troubleshooting. It is noteworthy that since the surgical environment enhances the difficulty of calibration, the algorithm is developed based on uncalibrated target coordinates.

Based on three original ideas, the EAS-based fault detection algorithm is developed. First, the EAS generated by the control framework amplifies the abrupt change of the jacobian matrix led by frozen motor faults and maps it to the measurable image velocity. Therefore, the frozen motor faults could be detected by monitoring image velocity, and the detectability is enhanced. Second, EAS adjusts state
strategies adaptively by introducing a barrier function, so that the states are kept from saturation. Third, EAS is merged with the signals that feedback errors and compensate depth. They constitute the controller so that the controller could not only generate signals utilized to detect faults but also stabilize the healthy system while preventing state saturation.

The contributions are twofold. First, this paper proposes a novel active fault detection method for sensor-less soft robot manipulators with state saturation prevention. The method monitors the system to detect frozen motor faults while keeping states from their boundaries in the visual servoing tasks. Second, with unknown parameters in EAS, the controller used in fault detection is extended to ensure the stability of healthy system while monitoring faults so that complicated off-line calibration of the target is avoided.

II. KINEMATICS MODELLING

A. Kinematics Model

The manipulator studied in this paper is shown in Fig. 1. Four cables are driven by four motors independently and are fixed on the ring embedded in the tip of the manipulator. By stretching cables, the manipulator deforms to the desired shape. Additionally, an endoscope is embedded in the central axis of the manipulator to capture images.

Based on the piecewise constant-curvature assumption, the homogeneous transformation matrix between the base plane and the tip plane, and the mapping between tip velocity and cable velocities are obtained.

$$ T(q) = T_0^1 T_1^2 \cdots T_{n-1}^n = \begin{bmatrix} R(q) & t(q) \\ 0_{3x1} & 1 \end{bmatrix} $$

$$ J(q) \cdot \dot{q} $$

where the length of cables, their derivatives, the rotation matrix, the translation vector, the transformation matrix, the jacobian matrix, linear and angular velocity of the end-effector are denoted by $q, \dot{q}, R, t, T, J, v$ and $\omega$ respectively.

B. Perspective Projection Model

Let $\Omega$ be the perspective projection matrix and $\Omega_i$ be its i-th row. Denote the 3D coordinates of the target with respect to the base frame, the camera frame and the end-effector frame by $x^b, x^c$ and $x^e$. The coordinates of the projection of the target on the image plane $p$ and its depth $z$ are obtained.

$$ p = \frac{1}{z} \begin{bmatrix} \Omega_1 \\ \Omega_2 \end{bmatrix} \cdot \begin{bmatrix} x^e \\ 1 \end{bmatrix} $$

$$ z = \Omega_3 \cdot \begin{bmatrix} x^e \\ 1 \end{bmatrix} $$

where $[x^b 1]^T = T_c^b \cdot [x^e 1]^T$.

Image velocity is the velocity of the target projection on the image plane, and it is the derivative of the image position $p$. Differentiating (3), image velocity $\dot{p}$ and the derivative of depth $\dot{z}$ are

$$ \dot{p} = \frac{1}{z} J_{im}(p, q) \begin{bmatrix} v \\ \omega \end{bmatrix} $$

$$ \dot{z} = J_{dep}(q) \begin{bmatrix} v \\ \omega \end{bmatrix} $$

$$ J_{im}(p, q) = \begin{bmatrix} \Omega_1^T \\ \Omega_2^T \end{bmatrix} - p \Omega_3^T $$

$$ J_{dep}(q) = \begin{bmatrix} -I_{3x3} & \text{skew}(R(q) x^b + t(q)) \\ 0_{1x3} & 0_{1x3} \end{bmatrix} $$

For simplicity, let $W(p, \Delta p, q) = J_{im} + \frac{1}{2} \Delta p J_{dep}$, where $\Delta p = p - p_d$ is the image error, $p$ and $p_d$ are coordinates of target projection and their desired value.

III. FAULT DETECTION MECHANISM

We propose a novel fault detection method. The method is to generate an endogenous accessary signal (EAS) and merge it with task error feedback to synthesize the controller and controls the soft robot manipulator system. The EAS maps the sudden change of the jacobian matrix led by faults to image velocity and amplifies it so that when faults occur, image velocity changes abruptly and remarkably, which enables them to be detected by directly measuring image velocity. Moreover, we put forward a barrier function in EAS that keeps states from their boundaries by adjusting the direction of control signals. Under the control of the EAS-based controller, faults are detected quickly and precisely while state saturation is avoided.

Applied to the soft robot manipulator, the EAS-based controller stabilizes the system while monitoring the faults.
When the fault happens, it leads to the abrupt change of image velocity due to EAS and is quickly detected. Then, the information of faults is identified by state estimation, and the fault-tolerant controller takes charge of the faulty system. The control diagram of the closed-loop system is shown in Fig. 2.

In this section, firstly, we set forth the design of the endogenous accessory signal and analyze the fault detection mechanism in subsection A. Secondly, we present the EAS-based controller that merges EAS with the image feedback in subsection B. Thirdly, we propose the fault identification method and fault-tolerant controller in subsection C.

A. Endogenous Accessory Signal

The critical point of this fault detection method is the EAS. It not only maps the abrupt change of the jacobian matrix to image velocity to enable faults to be detected but also adaptively adjusts the trajectory in state space to avoid saturation.

In the design of EAS, on the one hand, we introduce a matrix $N$ to establish a mapping between the jacobian matrix $J$ and image velocity $\dot{p}$; on the other hand, we propose a barrier function $f_b(q,N)$ that adjusts the state trajectory to avoid saturation. To ensure the EAS not to disturb the healthy system, the columns in $N$ is selected to be the non-zero vectors in the null space of the jacobian matrix $J$, which means $N \cdot J = 0$.

The EAS $\dot{q}_{eas}$ is designed as (8).

$$\dot{q}_{eas} = \frac{1}{1 + e^{-w}} f_b(q,N) N k_{eas} \| \Delta p \|$$  \hspace{1cm} (8)

where $k_{eas}$ is a positive gain and $w$ is a scalar used to adjust the weight of different signals.

In terms of a healthy system, the contribution of the EAS to the end-effector velocity $[v_{hs}] = [J_{hs} \omega_{hs}]$ is

$$[v_{hs}] = [J] \dot{q}_{eas} = -\frac{1}{1 + e^{-w}} f_b(q,N) J N k_{eas} \| \Delta p \| = 0$$  \hspace{1cm} (9)

which means the signal would not influence the end-effector velocity, and therefore, has no contribution to the image velocity.

However, under the frozen motor faults, the jacobian matrix $J$ suddenly changes to $J_f = J - J_i$, and the end-effector velocity contributed by EAS is given by

$$[v_{fs}] = [(J - J_i) \dot{q}_{eas} = -\frac{1}{1 + e^{-w}} f_b(q,N) j_i n_i k_{eas} \| \Delta p \|]$$  \hspace{1cm} (10)

where $J_i = [0 \cdots 0 j_i 0 \cdots 0]$, $j_i$ is the $i$-th column of $J$, and $n_i$ is the $i$-th element of the vector that composes $N$.

According to (2) and (10), the contribution of the EAS to the image velocity abruptly varies from $0$ to

$$\dot{p}_{fs} = \frac{1}{z} J_{im} \begin{bmatrix} v_{fs} \\
\omega_{fs} \end{bmatrix} = -\frac{f_b(q,N)}{z(1 + e^{-w})} J_{im} j_i n_i k_{eas} \| \Delta p \|$$  \hspace{1cm} (11)

The abrupt change of image velocity indicates the occurrence of frozen motor faults, and therefore, the fault could be detected quickly by monitoring the changing rate of image velocity.

The barrier function $f_b(q,N)$ is proposed to adjust the direction of EAS adaptively according to the distance between current cable lengths and their upper and lower boundaries. By adjusting the EAS direction, the state trajectory is changed and the state saturation is avoided. Denote the upper and lower boundaries of states by $q_{upb}$ and $q_{lwb}$, and the barrier function $f_b(q,N)$ is designed as (12), where $\Delta_t$ is the sample interval, $k$ is a positive gain and $q_i$ is the length of $i$-th cable. $d(q,N)$ measures the distance between the system states and their boundaries in null space, whose boundaries are $b$.

$$f_b(q,N,t + \Delta_t) = \frac{1}{2} f_b(q,N) + \frac{d-b}{\sqrt{d-b}2|d-b|d-b}$$

$$d(q,N) = \sum_{i=1}^{4} \left( q_{upb} - q_i \right) \left( q_{lwb} - q_i \right), n_i$$  \hspace{1cm} (12)

$$b = k \left( q_{upb} - q_{lwb} \right)$$  \hspace{1cm} (13)

In order to guarantee the existence of abrupt change of image velocity when frozen motor failures occur, the product of $j_i$ and $n_i$, $p_i(q) = j_i \cdot n_i$ is supposed to be non-zero for arbitrary $i$, since all motors have the probability of being frozen. To enhance the robustness of the fault detection method by keeping the states from the undesired ones that lead to zero $p_i(q)$, we extend the EAS as (15) by proposing an artificial potential field $U$.

$$\dot{q}_{eas} = \frac{1}{1 + e^{-w}} f_b(q,N) N k_{eas} \| \Delta p \| - K\partial U / \partial q$$  \hspace{1cm} (15)

$$U(q) = \kappa_1 \left( s_1^2(q) + \alpha_1 s_1(q) \right) + \kappa_2 \cdot s_2^2(q)$$  \hspace{1cm} (16)

where the column counts and row counts of the corresponding matrix are denoted by $cn(-)$ and $rn(-)$, the $m$-th minor of the jacobian matrix is denoted by $J_{m}$, $\alpha_1$ and $\alpha_2$ are very small positive constants, $K\partial U / \partial q$ is a positive-definite and diagonal matrix, $\kappa_1$ and $\kappa_2$ are positive gains and

$$s_1(q) = \sum_{i=1}^{cn(j)} \left| J_{m}(q) \right|$$  \hspace{1cm} (17)

$$s_2(q) = \prod_{i=1}^{rn(j)} \frac{1}{\left| J_{m}(q) \right| + \alpha_2}$$  \hspace{1cm} (18)

Differentiating (16), we obtain the potential force $\partial U / \partial q$.

$$\partial U / \partial q = \sum_{i=1}^{cn(j)} \left( 2 \kappa_1 s_1(q) + \alpha_1 \right) \frac{\partial \left| J_{m}(q) \right|}{\partial q}$$

which means in terms of those undesired states $q_{ud}$ that indicate the non-zero $|J_{m}(q)|$s or the zero $n_i(q)$, they lead to non-zero $s_1(q)$ or very large $s_2(q)$, and therefore, an enormous potential force that repulses states from the
subspace where one of \( n_i(q) \) is zero and attracts them to the subspace where \( |J_m(q)|_s \) are all zero. Therefore, with the artificial potential field (16) introduced, the states \( q \) are kept from their undesired value \( q \), and the existence of an \( N \) whose elements are all non-zero is guaranteed. By suitably choosing \( N, \ p_i(q) \) is ensured to be non-zero, and the image velocity would change abruptly no matter which motor is frozen. The robustness of the fault detection method is enhanced.

### B. Adaptive Controller Design

Considering the difficulties in conventional off-line target coordinates calibration in task space, we assume the 3D coordinates of the feature point with respect to the base frame \( x^b \) is unknown. In this subsection, a controller is put forward based on the EAS, and an adaptive law is proposed to update \( \hat{x}^b \), the estimation of \( x^b \). The stability of the system is proved using Barbalat’s Lemma.

According to (6) and (7), \( W \) can be represented in a linear form of the 3D target coordinates \( x^b \), which means for arbitrary matrix \( A \) and vector \( p \) that are independent of \( x^b \), there exists a regression matrix \( Y \) such that

\[
AW(x^b) \cdot \rho = Y \cdot x^b
\]

(20)

Merging extended EAS (15) with image feedback and depth compensation, the controller is designed as (21).

\[
\dot{q} = \frac{1}{1 + e^{-w}} p_b(q, N) N_{k_{eas}} \| \Delta p \| - K_{pf} \frac{\partial U}{\partial q} - \left( \left\| \frac{\partial U}{\partial q} \right\| - 1 + e^{-w} \right) \frac{1}{I_{cn(j)_{(j)cn(j)_{(j)}}}} J^T \hat{W}^T K_p \Delta p
\]

(21)

where \( \hat{W} \) is the estimation of \( W \), \( K_p \) and \( K_{cps} \) are positive-definite and diagonal matrix, and the gain matrix of the potential force \( K_{pf} \) is designed as

\[
K_{pf} = \| J^T \hat{W}^T K_p \Delta p \|^2 - I_{cn(j)_{(j)cn(j)_{(j)}}}
\]

(22)

By introducing a specific regression matrix \( Y \), \( J^T(W - \hat{W})^T K_p \Delta p \) could be represented as a linear form of \( \Delta x^b \), where \( \Delta x^b = \hat{x}^b - x^b \) is the estimation error of \( x^b \).

\[
J^T(W - \hat{W}) K_p \Delta p = Y \Delta x^b
\]

(23)

The corresponding adaptive law is designed as:

\[
\dot{\hat{x}}^b = \Gamma^{-1} Y^T \left( \frac{1}{1 + e^{-w}} J^T \hat{W}^T K_p \Delta p + K_{pf} \frac{\partial U}{\partial q} \right)
\]

\[
+ \left\| \frac{\partial U}{\partial q} \right\| \cdot K_{cps} J^T \hat{W}^T K_p \Delta p
\]

(24)

Multiplying \( \Delta x^b \) from left to the adaptive law, we obtain

\[
\Delta x^b \Gamma \dot{\hat{x}}^b = \frac{1}{1 + e^{-w}} \Delta p^T K_p(W - \hat{W}) J^T \hat{W}^T K_p \Delta p
\]

\[
+ \left\| J^T \hat{W}^T K_p \Delta p \right\| \Delta p^T K_p(W - \hat{W}) J \frac{\partial U}{\partial q}
\]

\[
+ \left\| \frac{\partial U}{\partial q} \right\| \Delta p^T K_p(W - \hat{W}) J K_{cps} J^T \hat{W}^T K_p \Delta p
\]

(25)

The candidate of Lyapunov function is selected as follows:

\[
V(t) = \frac{1}{2} \Delta p^T K_p \Delta p + \frac{1}{2} \left( \Delta x^b \right)^T \Gamma \Delta x^b
\]

(26)

whose derivative is

\[
\dot{V} = \Delta p^T K_p \hat{W} \dot{q} - \Delta p^T K_p \left( W - \hat{W} \right) J \frac{\partial U}{\partial q} + \left( \Delta x^b \right)^T \Gamma \Delta \dot{x}^b
\]

(27)

Note that

\[
- \Delta p^T K_p \hat{W} J \frac{\partial U}{\partial q} = -\| J^T \hat{W}^T K_p \Delta p \|^2 \cdot \Delta p^T K_p \hat{W} J \frac{\partial U}{\partial q}
\]

(28)

\[
\leq \Delta p^T K_p \hat{W} J \| \Delta p^T K_p \hat{W} J \| \| \frac{\partial U}{\partial q} \| \| J^T \hat{W}^T K_p \Delta p
\]

We select a gain matrix \( K_{cps} \) whose minimum eigenvalue \( \lambda(K_{cps}) \) is greater than \( \lambda(K_{eas}) \).

Combining (21), (22), (25), (27) and (28), we have

\[
\dot{V} \leq -\frac{1}{1 + e^{-w}} \Delta p^T K_p W J J^T \hat{W}^T K_p \Delta p
\]

\[
- \Delta p^T K_p \hat{W} J \| \Delta p^T K_p \hat{W} J \| \| \frac{\partial U}{\partial q} \| \| J^T \hat{W}^T K_p \Delta p
\]

\[
- \Delta p^T K_p \hat{W} J \left( K_{cps} - \| J^T \hat{W}^T K_p \Delta p \| \cdot I_{4 \times 4} \right) \cdot \| \frac{\partial U}{\partial q} \| \| J^T \hat{W}^T K_p \Delta p
\]

\[
\leq 0
\]

(29)

From (29), since the non-negative Lyapunov function \( V(t) \) is monotonically non-increasing, it is upper bounded, so that image errors \( \Delta p \) and estimation errors \( \Delta x^b \) are bounded, according to (26). With bounded \( \Delta p \) and \( \Delta x^b \), cable velocities \( \dot{\hat{q}} \) are bounded from (21), which implies \( \dot{V} \) is uniformly continuous. From Barbalat’s Lemma, we conclude that

\[
\lim_{t \to \infty} J^T \hat{W}^T K_p \Delta p = 0
\]

(30)

Denote the rank of the corresponding matrix by \( r(\cdot) \). By rank factorization, \( J = J_L : J_R \), where \( J_L \) is an \( (J) \times (J) \) matrix, \( J_R \) is a \( (J) \times cn(J) \) matrix, and both of their ranks are \( r(J) \).

With a full-rank \( \hat{W} \):

\[
r \left( J_R^T J_L^T \hat{W} \right) \leq cn(J_L) = 2
\]

\[
r \left( J_R^T J_L^T \hat{W} \right) \geq r \left( J_R \right) + r \left( J_L^T \hat{W} \right) - cn(J_L) = 2
\]

which means,

\[
r \left( J_R^T J_L^T \hat{W} \right) = 2
\]

(31)

Hence, image errors finally converge to zero.

\[
\lim_{t \to \infty} \Delta p = 0
\]

(32)

In conclusion, the proposed EAS-based controller can stabilize the system and make image errors converge while
monitoring the occurrence of frozen motor faults. If frozen motor faults happen, the EAS generated by the controller will lead to an abrupt change of image velocity that is directly observed and measured so that the failure could be detected precisely and quickly.

C. Fault Identification and Fault-tolerant Control

With failures detected, they are supposed to be identified so that the fault-tolerant control strategies could be activated based on the information of failures.

The fault identification algorithm is developed based on the Extended Kalman Filter (EKF). When frozen motor faults occur, they are quickly detected, and the fault identification algorithm is activated. In each control loop, EKF is utilized to estimate the system states (cable lengths) with the control signals and image errors input. After certain loops, the estimations of states are compared with the ones that are calculated by assuming no faults occur. The cable that owns the maximum difference is identified as the faulty one, and its length is set to be the real value.

Based on the identified failure information, the fault-tolerant control scheme is proposed.

\[ \dot{q}_{f1} = \Sigma J^T \hat{W}^T K_p \Delta p \]  

(33)

\[ \dot{x}_f^b = \Gamma^{-1} Y^T \Sigma^2 J^T \hat{W}^T K_p \Delta p \]  

(34)

where \( \Sigma \) is diagonal and

\[ \Sigma_{ii} = \begin{cases} 0, & \text{\textit{i}–th motor is frozen} \\ 1, & \text{\textit{i}–th motor is not frozen} \end{cases} \]  

(35)

By combining (33) and (34), we differentiate the Lyapunov function candidate (26) and obtain

\[ \dot{V} = \Delta p^T K_p W J \Sigma \dot{q}_{f1} + \left( \Delta x^b \right)^T \Gamma \Delta x_f^b \]  

(36)

\[ = -\Delta p^T K_p \hat{W} J \Sigma^2 J^T \hat{W}^T K_p \Delta p \leq 0 \]

The monotonical non-increase of \( \dot{V} \) implies the boundedness of \( V, \Delta p \) and \( \Delta x^b \), which means the \( \dot{q} \) is bounded and \( \dot{V} \) is uniformly continuous. Therefore,

\[ \lim_{t \to \infty} \Sigma J^T \hat{W}^T K_p \Delta p = 0 \]  

(37)

With a frozen motor, one of the elements on the diagonal of \( \Sigma \) is zero. As stated in section III, because there are not zero elements in the vectors that compose the basis of the null space of the jacobian matrix, arbitrary \( cn(J) - 1 \) rows in \( J^T \) are independent. Therefore, the rank of \( \Sigma J^T \) is

\[ r \left( \Sigma J^T \right) = r \left( J^T \right) = \min \{ cn(J), rn(J) \} - 1 \]  

(38)

As similar to the proof given in (31), by rank factorizing \( \Sigma J^T \), the matrix \( \Sigma J^T \hat{W}^T \) is proved to be full-rank and

\[ \lim_{t \to \infty} \Delta p = 0 \]  

(39)

which means the fault-tolerant controller can stabilize the system and make image errors converge to zero even though a frozen motor fault has happened.

IV. EXPERIMENTS

To verify the performance of the proposed method, we conduct experiments on a 240 mm long manipulator (as shown in Fig. 3) whose diameters of the tip and base plane are 16 mm and 25 mm, respectively. The shape of the soft robot manipulator is decided by four cables that are fixed on its tip and driven by four independent motors. Cable velocities are the output of the controller, and cable lengths are obtained by integrating cable velocities. Image positions are obtained by image processing, and image velocities are calculated by differentiating the image positions. Two experiments are conducted to validate the performance of the proposed method in healthy system and faulty system, respectively.

In experiments, the control gains are \( w = 2.3, k = 4, k_{eas} = 1.5 \times 10^{-7}, K_{cps} = 9.0 \times 10^{-13}, K_p = 4.0 \times 10^{-11}, \Gamma = 1 \times 10^{-4}. \) The perspective projection matrix is

\[ W = \begin{bmatrix} 708.48 & -305.51 & 385.79 & 0 \\ 289.37 & 743.09 & 207.87 & 0 \\ -0.096 & 0.0087 & 0.9953 & 0 \end{bmatrix} \]

The upper and lower boundaries of the states are \( q_{upb} = 25 \text{mm} \) and \( q_{lb} = 5 \text{mm}. \) \( N_J \) is chosen as \( N_J = \frac{1}{2} \begin{bmatrix} 1 & -1 & 1 & -1 \end{bmatrix}^T \) and the desired position of the target projection on the image plane is \( p_d = \begin{bmatrix} 250 & 150 \end{bmatrix}^T \text{pixel}. \)

In the first experiment, we validate the performance of the methods in healthy system. The saturation-prevention controller proposed in [13] and the EAS-based controller proposed in this paper are compared. Similar to this research, [13] utilizes the redundancy of manipulators to adjust joint variables to avoid saturation. However, the adjustment strategy is different. The controller proposed in [13] is designed as \( \dot{q} = J^s(q) \dot{x} + (I - J^s(q) J(q)) \dot{q}_N, \) where \( J^s(q) \) is the pseudoinverse of the jacobian matrix \( J(q), s \in (0,1) \) is a task scaling factor, \( \dot{x} \) is the velocity in task space (a mapping from image errors \( \Delta p \) to end-effector velocity in this paper).
and \( \mathbf{q}_N \) is a null-space velocity vector. The strategy is that when one of the system states \( \mathbf{q}_i \) approaches its boundary, the scaling factor \( s \) is reduced to put aside the task and facilitate recovery feasibility. \( \mathbf{q}_N \) is designed to adjust the corresponding system state in the null-space to keep it away from its boundary. Fig. 4 (a) and (b) plot the image errors and cable lengths. The data of the EAS-based method are plotted by real lines, while the ones of the conventional method are plotted by dashed lines. Indicated by Fig. 4, both of the two methods keep system states from their boundaries, stabilize the system, and converge image errors. However, the EAS-based method owns the superiority that it could avoid state saturation while monitoring the health condition of the system, compared with the conventional method.

The second experiment is conducted to validate the performance of the proposed method under frozen motor faults. The second motor is frozen at 1.5 second. Image errors, image velocity and length of cables are shown in Fig. 5 (a), (b) and (c), respectively. As shown in Fig. 5 (b), when the fault occurs, the image velocity increases remarkably and abruptly by adopting the EAS-based method. Its change rate increases from 130.02 pixels/s\(^2\) to 962.94 pixels/s\(^2\), where its maximum change rate in the previous history is merely 286.87 pixels/s\(^2\). The change rate is 335.67% of the previous maximum one and implies the occurrence of the fault. The time cost of fault detection is 0.1 seconds. After 1.5 seconds, the fault is identified and the fault-tolerant controller takes charge of the system. Eventually, image errors asymptotically converge to zero.

### V. CONCLUSION

This paper proposes a novel EAS-based fault detection method as an improvement of the conventional method and applies it in the visual servoing task of a soft robot manipulator. The method is extended by introducing a barrier function that generates force to adjust the EAS direction so that it keeps the trajectory of states from its boundaries. Additionally, with uncalibrated feature point, an adaptive algorithm is developed to ensure the convergence of image errors in healthy system. Experiments validate the performance of the proposed method in both normal and faulty modes. The disadvantage of the method is that the method is kinematics-based, which means the uncertainty and disturbance from dynamics are ignored and we will investigate this challenge in future research. Moreover, cooperating with other algorithms, for example, image scene recognition algorithms \([14]\) and contact force estimation algorithms \([15]\), enhances the usefulness of the proposed fault detection method when handling moving targets and complicated surgical environments.

### REFERENCES


