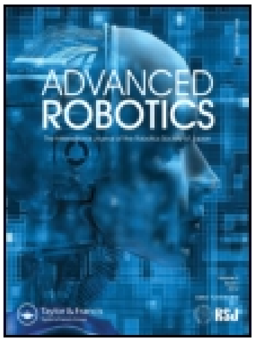

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M.T. Hussein

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SURVEY PAPER

A review on vision-based control of flexible manipulators

M.T. Hussein*

Mechanical Engineering Department, University of Babylon, Hillah, Babylon, Iraq

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In this review, recent developments in the field of flexible robot arm control using visual servoing are reviewed. In comparison to rigid robots, the end-effector position of flexible links cannot be obtained precisely enough with respect to position control using kinematic information and joint variables. To solve the task here the use of a vision sensor (camera) system, visual servoing is proposed to realize the task of control flexible manipulators with improved quality requirements. The paper is organized as follows: the visual servoing architectures will be reviewed for rigid robots first. The advantages, disadvantages, and comparisons between different approaches of visual servoing are carried out. The using of visual servoing to control flexible robot is addressed next. Open problems such as state variables estimation as well as the combination of different sensor properties as well as some application-oriented points related to flexible robot are discussed in detail.

Keywords: flexible robot; visual servoing; camera sensor; state estimation

1. Introduction

Robots are widely applied in various areas, especially in industrial assembly processes. One major source of uncertainty that often leads to poor performance or even failure of the assembly tasks is the absolute motion control used in the conventional robotic systems.[1] Using this type of control, the target object is required to be accurately placed at fixed world coordinate frame, and therefore, only absolute pose (3D position and orientation) of the robot end effector in the base frame is controlled to operate with respect to the target object. Usually, the robot joint encoder is the only available measurement in rigid manipulator system. So the operation can be affected by uncertainty or errors regarding the pose of the robot end effector or target object, e.g. due to robot calibration errors, lack of link stiffness, and unpredictable target motion. These conflicting requirements between high speed and high accuracy lead to the use of flexible robots.

Here, the challenge lies in the incorporation of flexibility effects in the system model leading to increase in complexity which, in turn, complicates the problem of controller synthesis. Due to the flexibility, the controller must be able to control the motion of the rigid-body mode of the arm and to suppress the vibration modes. Flexible link robots are distributed parameter systems and have an infinite number of degrees of freedom; hence many researchers have tried to solve the control problem by improving the dynamic models and incorporating different control strategies. Due to the structural flexibility of flexible robots, specific control approaches are required to affect their vibrations. Another difficulty with such systems is that the preparation of the robot for new tasks requires considerable reprogramming effort.[2]

In order to overcome the above issues, a straightforward solution is to add additional sensors to the flexible robots control system, which can directly measure the relative motion between the robot end effector and the target, and at the same time can also measure the vibration in the flexible link. Vision sensors are cheap, may have specific high accuracy; versatile sensors are well suitable for a wide range of robot control. This has been one of the major research areas in robotics for more than two decades. The task of flexible robot visual servoing is to control the pose of the robot end effector relative to either a world coordinate frame or a target object being manipulated, and to damp out the vibration in the structure by implementing real-time image measurements extracted from the distinguishable visual features.

This paper is organized as follows. Section 2 describes the general vision-based control process. Visual servoing approaches are addressed in Section 3. In Section 4, visual servoing of flexible robot is discussed in detail. Applications and classification of visual servoing of flexible robot is detailed in Section 5. The state of art is summarized in Section 6.

*Email: eng.mustafa.turky@uobabylon.edu.iq

2. Vision-based control

Machine vision,[3] which is originated from photogrammetry, is thought to have the ability to sense, store, and recover a virtual space that matches the original space as closely as possible. Based on photogrammetry, machine vision technologies expanded into new research areas such as object recognition. The application of machine vision in robotics is robot vision (visual servoing), which concentrates on recognition, positioning, inspection, and modeling of objects. Two questions about the objects what ...? (recognition) and where ...? (precision) could be solved using the vision system [1]; in robot applications, it should solve both of them. It is often focused to one of these two aspects, to realize the robot system to solve tasks of recognizing special objects (marks) or to evaluate its movement accuracy relative to the environment. In Figure 1, a typical robot vision procedure based on the characteristics of robot applications is presented. Different parts of this procedure could be investigated to produce various practical technologies suitable for different applications. The elements in Figure 1 represent: 3D world (object), the vision data 2D (image), the data extracted from 2D image (features), the 3D model description of objects or targets (interpretation), the camera (vision system), the image processing (feature extraction), transformation from 2D to 3D algorithm (reconstruction), and the method giving the decision about how to use the results from all elements (control model).[3] This typical form of the robot vision system can be adjusted based on the following factors: the kinds of images required, features found in the images, the mathematical form of these features as obtained from the images, and how to use the image features recovering the observed objects.

3. Visual servoing system

In 1979, visual servoing is introduced by [4], in order to distinguish a new control approach. This technology merges the vision information into the usual control loop of a robot. This type of control system is not only a simple feedback system but a result of the fusion of many areas such as high speed image processing, kinematics, control theory, and real-time computing.[1,5] Incorporated with sensor fusion technology, many vision-based controllers have been investigated which realizing industrial, surgical, space, and military applications. The kinematics-based methods work with the assumption that the velocity of the manipulator can be controlled precisely. While dynamic visual servoing directly provide joint inputs based on visual feedback and the nonlinear robot dynamics. The visual servoing methods have been briefly discussed, compared, and reviewed by many researchers [1,5–8]. Visual servoing systems were classified with respect to several aspects:

- the position of the camera as eye-in-hand and eye-to-hand [5];
- the feedback representation mode position-based, image-based, and hybrid visual servoing [8];
- the combination of vision sensor and controller of the joint: dynamic look-and-move system and direct visual servo system [8]; and
- the use of the visual information (control model) distinguishes two types of visual servoing systems: kinematics-based visual servoing and dynamic visual servoing,[9]

in this review only the characteristics and drawbacks of the methods will be presented.

3.1. Position-based visual servoing

The 3D visual information used in position-based visual servoing (PBVS), define the position and orientation of the object (target) with respect to the camera (robot) coordinate system as a desired reference input. Figure 2 shows the basic block diagram for PBVS system. Here, ${}^{C}P_T$ is the target pose with respect to the camera, and ${}^{C}P_T^*$ is the desired target pose. The error between the desired pose and the pose of the target represent the motion required to move the robot from its initial pose to the desired pose. The position-based methods have been investigated and discussed by many researchers [10–13].

The practical applications of this method have the advantage that it allows the error computation from the desired relative pose in the 3D workspace. The second advantage is that the end-effector Cartesian trajectory can be controlled to move along a straight line in the Cartesian space. In addition, the controller design can use the advantage of classic robot control problem; due to the separation of the pose estimation problem from the control design problem.[1] One of the inherent problems of the position-based method is that the geometric model of the object should be known for pose estimation,[14–16] which makes it a "model-based" method in comparison with the image-based method. The second problem related to PBVS is the sensitivity of the camera calibration error; the camera calibration is needed to get the unbiased Cartesian positioning.

3.2. Image-based visual servoing

The image-based visual servoing (Figure 3) defines the desired reference input using the 2D visual information (image features). In image-based visual servoing (IBVS), the relative pose is estimated based on the features f provided by the camera. The control goal is fulfilled by coinciding the desired f^* and estimated f features. In this method, control error function is computed in the 2D space based on the image Jacobian matrix that shows the characteristics of movement in image space. The image-based method have been investigated and discussed by many researchers [7,8, 10,14,15,17]. The practical advantage of this method is that

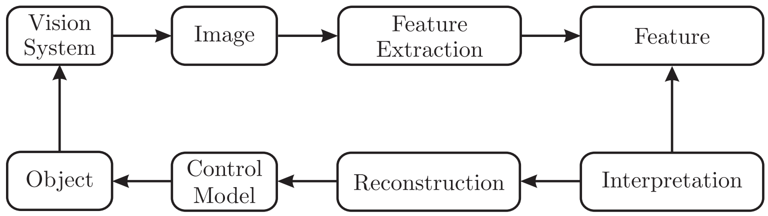

Figure 1. General vision-based control procedure.

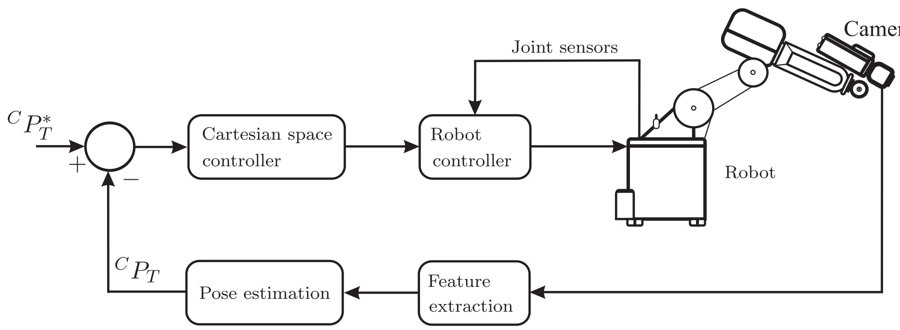

Figure 2. Position-based visual servoing.

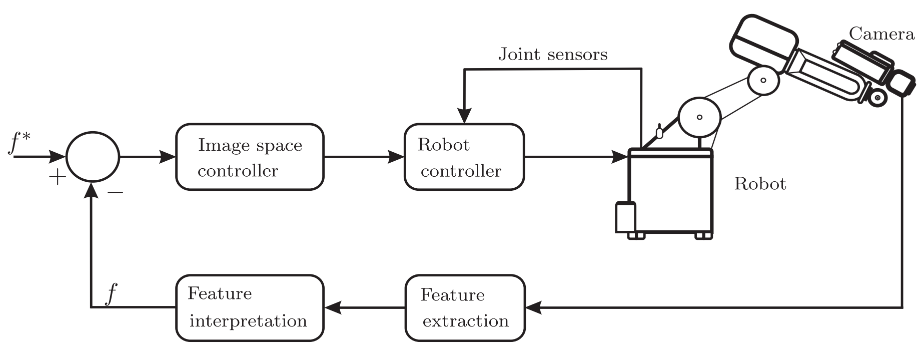

Figure 3. Image-based visual servoing.

it represents a "model-free" method, this means there is no need for a full object model and also no camera model. The positioning accuracy of the image-based method is robust to the camera and target modeling errors.[7,15] The stability of the image-based method is known to be robust with respect to camera calibration errors.[17] The major disadvantage of the image-based method is that it is local asymptotic stable, where the control error function decreases exponentially.[5,10] It has been stated in [14] due to the coupling between the end-effector translational and rotational motions, the image-based visual servoing suffers from typical problem representing the motion coupling, when the camera moves away from the target in a depth direction and then returns (camera retreat). Also in the presence of camera modeling errors, the analytically described robustness domain of the stability of the system dynamics cannot be determined due to the fact that the system is highly coupled.[14,17] There are disadvantages of existing image singularities and image local minima induced from the image Jacobian matrix, which may lead to potential failure of the method.[5] These control law drawbacks arise especially when the initial and the goal camera images, respectively, corresponding to the actual and desired system configurations are very different (i.e for large system displacements).

3.3. *Hybrid visual servoing approach*

Using the advantages of both of the two earlier approaches and in order to overcome their disadvantages, a hybrid visual servoing ($2\&\frac{1}{2}$ D) which represents a new visual servoing system is presented by [16]. Hybrid visual servoing represents a system which does not need a complete 3D model of the object, and also can be used in the whole work space of the system. Several hybrid visual servoing approaches (HVSA) have been proposed.[16,18,19] The aim is to get HVSA which gives a partial control in the same time for both of Cartesian and image trajectories. This approach realizes model-free visual servoing; it still uses the recognizable feature in the image but does not require a full object model. Unlike to image-based approaches, the analytical robustness domain of system dynamic stability can be determined, in other words, camera modeling errors can be expressed by closed form analytical function. Finally, this method is free of singularities and local minima.

Another hybrid approach is the partitioned approach in [20]. Within the approach, the rotation around and translation along the optical axis from all other DOFs are decoupled. This is specifically developed to avoid problems related to a pure rotation around the optical axis. Although the partitioned approach is a very suitable method to keep the object in the field of view, this method has one drawback: the two IBVS rotational degrees of freedom are controlled in image space, they do not take Cartesian space into account.[21] Another work which executes visual control by combining or partitioning the visual control structure which is the methodology of switching control is presented in [6], the method allows switching of the controller (i.e. switching between IBVS and PBVS) based on the situation of the system or based on measurements in image space. The switching control encompasses the idea that in each iteration, it should be decided which controller should be used, based on the performance criteria.

In the last decade, many researchers proposed several developments for visual servoing to overcome the drawbacks of previous developed approaches. A virtual visual servoing enabling the calculation of camera parameters iteratively is proposed in [22]. Using a special calibration rig [23] investigated a calibration method to determine varying intrinsic parameters. Fuzzy techniques are used to estimate the robot-camera model [24] which presents a new eye-to-hand visual servoing method using inverse fuzzy modeling. This method can be used with unknown camera and/or robot parameters. Shen and Yin [25] also used a fuzzy controller and applied it on a specific class of IBVS. Here the camera moves in the depth axis, for the sake of finding the image moment to reflect the object depth.

A new method for image-based visual servoing approach with eye-in-hand configuration and not calibrated camera parameters proposed in [9,26,27]. Depth independent interaction matrix have been developed and extended, the asymptotic stability of this method has been proved using Lyapunov theory. The asymptotic stability condition is the elements result from multiplication of depth interaction matrix and its inverse are greater than zero. The inverse of depth interaction matrix-approximated model is determined using offline step. The interaction matrix and the depth are updated at each iteration using the measurements of the features. Each feature is constrained to reach its desired position through straight line. In these studies, a new algorithm has been developed to estimate the unknown camera and geometric parameters. An introduction to sensor fusion approach using a combination of two cameras (eye-in-hand and eye-to-hand) is presented by [28]. The approach reduces the inaccuracy of the estimation of the end-effector pose. As a result, the robustness of visual servoing is improved. In recent years, many problems in visual servoing got more and more attention from the researchers. There are many points related to the visual servoing need further studies, e.g. stability analysis of visual servoing systems, uncalibrated visual servoing, time delay in the measurements, sensor data fusion, and stereo visual servoing.

4. Visual servoing of flexible robots

A vision sensor (camera) represents a contactless virtual movable measurement sensor, or a set of sensors working at the same time (i.e. getting a set of data from the camera), therefore vision-based control can improve the control performance and can be extended to other application areas such as flexible robot manipulators. In the last three decades, the researchers stimulated to study flexible manipulators due to the need of large load capacities, low energy consumption, the use of small actuators, the requirements related to high speed, and also to high precision robot's operations. Recently there has been an increasing research interest in this area. A number of research reports concentrating in visual servoing of flexible robot applications have been published in order to study the related issues (see applications in Section 5).

Flexible robots have been employed not only in space shuttles but also in industrial, surgical, and maintenance applications. However, due to the structural flexibility and inertial forces, flexible robots have very complex static deflections, they show dynamic vibrations, especially in high-speed operations. Static deflection adds the initial condition value to the system which should be taken into account in the control design process. In many cases, there will be very large path tracking or positioning errors. The dynamic models of flexible robot available till date cannot take care of large elastic deflections of the manipulator. Internal resonances due to modal interactions are almost ignored, and in most analyses of multi-link manipulators, only linearized models are considered.[29] Many control techniques were proposed to isolate the dynamic errors based on the dynamics models,[29] but they seem not very suitable for real-time application due to the very complicated and time-consuming computation of the dynamics of flexible manipulators. Compared to rigid robots the end-effector position of flexible links cannot be obtained precisely enough based on the kinematics and joint variables, because the position of any point of a flexible link is not only related to the joint angles but also to the link flexural displacements.

4.1. State variables estimation of flexible robot using vision sensors

In case of rigid manipulators, the state variables consist of joint angles and their velocities, which can be measured by encoders, potentiometers, tachometers, and so on. In case of flexible manipulators, however, the state variables also include elastic deformations and their velocities due to flexibility. In order to control a flexible manipulator based on dynamic model, the state variables should be accurately estimated.

Flexible link robots are distributed parameter systems and have an infinite number of degrees of freedom. Each degree of freedom can be represented using time-related variable and flexible mode shape function. A mode shape function represents the shape of the beam related to a specific natural frequency. This mode shape can be determined by the eigenvalue problem of the vibration equation. In flexible link robot case, the modes are modeled using elasticity theory in order to describe the shape of the link. In general, the frequencies of the individual modes have no simple relation to each other. For control purposes, the approximation of the dynamical behavior is typically truncated to a finite number of flexible modes.[30] To sense these modes, the sampling frequency has to be at least twice the frequency of the highest mode of interest. Further, the vision system resolution needs to be high enough in order to detect the small vibration amplitudes of higher modes.[31] The work on vision-based control for flexible robot is first presented in [32]. The image feedback of the tip displacement and estimated vibration states are used in [32] to improve the overall performance of end-effector position control. The main disadvantages of this work are the limited abilities of data processing and analyzing, camera properties, and image processing software. Several image processing schemes are proposed by [32] to increase the operational speed. The researchers had overcome these disadvantages in the following years through the generation of powerful processing and new vision systems. In [33], the camera is used to measure the state variables of flexible link, and then these measured states are used to identify the physical parameters of flexible link dynamic model. The idea is to use the camera sensor to measure the real elastic deformation related to markers along the link and transform these positions (markers position) as virtual passive joint angles.

The issues of vibration measurement and control, the end-effector trajectory tracking control, and Cartesian space trajectory tracking control of robot arms with link flexibility using vision sensor data are addressed in [34–36]. The control strategies used are: regulation of end-effector trajectory tracking error to zero based on visual feedback, compensation of nonlinear forces, and to damp out the vibrations of the flexible links using a PD plus controller based on feedback of link deflections. Since the time derivatives of the end-effector position, joint angles, and link deflections are needed in calculation of the control input, the estimation algorithms are used to estimate the value of the velocities in order to calculate the control input.

4.2. Output feedback control of flexible robot using vision sensors

As an alternative to state feedback control method, the camera is used as a sensor to measure the output of the system and provide the controller with the information about the target in order to generate the required input. In [31,37], a landmark tracking system-based position sensor with fast sampling rate and good position resolution was proven effective and economical. With this sensor, the first two natural modes of the studied long-reach manipulator were identified. The direct sensing of the endpoint position of a flexible positioning system using this sensor can provide a feedback signal that can always ensure accurate tip placement. The landmark tracking system works even with link inaccurate construction and in the case of uncertain placement of equipment. The analytical criteria for selection of the number, type, and location of suitable sensors for robust control of mechanical systems with flexible bodies are presented in [38]. In the criteria, a dynamic sensors data fusion approach is developed to integrate additional sensors such as vision-based sensors in the active control of flexible robots.

The eye-in-hand IBVS of flexible manipulators is studied in [39]. The IBVS approach was chosen as it computes the feedback control directly from the visual information, and does not require any further knowledge of the physical parameters of the manipulator. In [39], the IBVS approach is implemented by combining the two-time scale control of flexible structures and the task-space control. Dynamic effects of both the rigid and the flexible motion of the manipulator are fully taken into account. The "fast" subsystem uses the joint sensors information, while the visual information is used in the "slow" subsystem for a task-space-oriented control law. Since the control law in this case is related to work space, the computationally expensive operations such as generating the inverse and also the time derivative of the Jacobian, are avoided. The results related to this approach are simulated and implemented experimentally in [39–41].

4.3. Sensor data fusion

In the last decade, the problem of data fusion sensor (i.e. strain gage, vision sensor, $\cdots$) in the control of flexible link robots, is strongly addressed by several researchers. The vision sensor data can be used effectively in cooperation with other types of sensors for control of the flexible robot system due to the versatility of vision sensor. Nowadays, the vision sensor can be represented as set of sensors and not only as plain visual feedback. Several measurements can be accomplished in the same time using single vision sensor (i.e. the same image frame) by augmenting the image processing software and without needing to change the sensor position.

The estimation of the elastic coordinates as a problem of sensor data fusion is presented by [42]. Although Kalman filter can be effectively used to weigh the measurements coming from different sensors, the approach developed in [42] allows the design of a complete visual servoing control law which can be applied using a digital camera, a standard image acquisition, and processing hardware. Three-dimensional range sensor is proposed in [43–45] for estimating the vibration of large scale flexible structure. In this scheme, a set of synchronously working satellites is employed to observe the vibrations that appear in various parts of the structure. The measured vibrational data range from the satellites are fused using Kalman filter. This method is validated by experiment where stereo camera is used as the range sensor in order to estimate the vibration of a quadruple pendulum composed of four links and low-friction rotational joints. The method presented consists of three parts: kinematic data fusion, Kalman filtering, and shape estimation. The advantage of this method is that it needs only coarse kinematic surrogate measurements to be provided to the Kalman filter, but on the other hand, it assumes that the dynamic model is accurately known and the mode shapes are approximately known a priori.

4.4. *Improving the control of flexible robot using vision sensors*

The most common problems related to vision sensors are that of the noise and time delay of measurement data. Thus, the less noisy measurement from the camera can help improving the quality of deflection measurements. On the other hand, to deal with delays in a control system, the actuator gains should be increased to increase the damping and making the system more robust against the time delays. However, some approaches are not based on time delay robust controllers but on the accurate estimation of the delay itself. The vision-based two-time scale controller (fast and slow) to track a desired tip position while suppressing oscillations in the single flexible link is described in [46]. The vision sensor (slow) is used in combination with motor encoder (fast) to estimate the full states of the system. The effect of noise is removed using a Kalman filter, and the time delay effect is accounted using the dynamics of the system. The information obtained from end-effector camera (eye-in-hand) used by [47] to estimate the tip vibration using modified two-time scale Kalman filter takes into account the constant delay due to the image processing time. The estimator is modified in order to deal with image features of unknown objects. The image Jacobian matrix used in measurement equation cannot be obtained easily when no prior information available for the detected image features. In [48], two-time scale Kalman filter is used considering a variable delay which is estimated on the basis of timestamps. The variable time delay estimation based on timestamps represents a robust method against visual sensor troubles such as partial occlusions or failure of the camera sensor. The problem by considering sinusoidal regression instead of a Kalman filter to reconstruct the vibration from visual data is addressed in [49]. Using a eye-in-hand configuration, the problem of vibration suppression using visual features without any markers, or prior knowledge on the environment is developed by the authors of [49]. The tip displacement induced by vibrations is estimated exploiting a simple physical model of the manipulator.

The time delay was estimated in [48,49] by exchanging timestamps between real-time high sampling rate controller and the nonreal-time supervisor whose sampling rate is aligned to the camera frame rate. An alternative method described in [50] consists of using a secondary concurrent sensor to estimate the delay. The cross-correlation technique is used to compute the time delay between the two signals. These signals are: the first, free of noise but delayed visual data to estimate the tip displacement and the second is noisy, but concurrent inertial data to correct these visual data in time. An approach to combine suitable measurement devices easy to realize with improved reliability was proposed in [51]. In this work, the compensation of time delay and noise effects in the estimated states of the flexible link dynamics is addressed. The approach is based on the combination of the two estimated fast and slow dynamical parts of the flexible link dynamics by combining the estimations of the slow observer (based on vision measurements) with those of the fast observer (based on strain gauges).

5. Applications

As has been pointed out before, flexible manipulators can find many applications, but since the main problem is to control their vibrations, many researchers have tried to solve this problem by improving the dynamic models and incorporating different control strategies. The study on the control of a flexible arm manipulator started as a part of the space robots research, as a space manipulator should be as light as possible in order to reduce its launching cost. Another application for large robotic manipulators are needed in nuclear maintenance, e.g. to perform decontamination tasks. The nozzle dam positioning task for maintenance of a nuclear power plant steam generator is an example of a task that requires a strong manipulator with very fine absolute positioning accuracy.

In order to ease the design procedure of flexible space robot systems, a method developed in [38] to select the type and the location of sensors for flexible robotic applications is used. The sensors meeting these criteria are called 'hyperstability sensors'. The criteria are implemented practically on special three revolute joints and a very flexible link designed to simulate the dynamic characteristics of space station remote manipulator system. A control positioning for flexible link using camera space manipulation (CSM) is developed in [52]. In comparison with the visual servoing method presented by [38], CSM provides a less computationally intensive method which is imperative for flexible manipulation. Also, the amount of image data required for CSM makes it a vigorous method for unknown environments.

Any visual servoing systems using typically one of the two camera configurations: (1) eye-in-hand and (2) eye-to-hand configurations. The detailed applications for visual servoing of flexible manipulator are described below.

5.1. Eye-in-hand configuration

Despite of the structural flexibility of flexible manipulators, the eye-in-hand vision-based control which is more complicated than the eye-to-hand approach is addressed by many researchers in the last 10 years due to the development of the vision systems and controllers. The concept of the eye-in-hand is used in [53,54] to design an automated object capturing with a two-arm flexible manipulator. In this work, basic technology in space for automated object capture with a two-arm spatial flexible manipulator is presented. A small CCD camera and a laser displacement sensor are mounted at the end effector of the arm. The camera is utilized to detect the distance to an object and relative orientations at long and middle range, while the laser displacement sensor precisely measures the distance from each end effector to the surface of the object at close range. Feature-based visual servoing is applied to control the end-effector positions relative to the object positions.

In [55], the eye-in-hand approach is used to control the position of a flexible robot end effector. In [55], the flexibilities of the manipulator links are assumed as small disturbances to be counteracted by the feedback control loop. A vision-based training for a neural network control model of a planar, large-deflection robot manipulator is developed by [56]. The training data are acquired from images by moving the motors to a randomly selected motor position. This method which requires no previous knowledge of the kinematics or dynamics of the manipulator suffers from several disadvantages: not robust to sudden disturbances, time-consuming process of training the neural network, and it is applicable only on planar robot. An approach which is composed of an end-effector position control based on eye-in-hand visual servoing and a vibration suppression control is proposed in [57,58]. High- and low-pass filters are used to decouple the end-effector position control and the vibration control. This modified approach applied practically based on an impedance control used with 3D flexible link manipulator which succeeds to insert the peg into the hole whose clearance is 0.1 mm. In [58], also studied the trajectory and vibration control by using an endpoint camera, where a two-time scale discrete Kalman filter is used to estimate the deflection and vibration of the links using the endpoint camera.

Most of the vibration control strategies proposed so far assume that the structural vibration is directly measured (or it can be measured) by sensors such as strain gages or accelerometers. Specific applications such as articulated inspection arm (AIA),[59] which works in high temperature and high level of radiation, need special type of sensors. The eye-in-hand camera system used in incorporation of other sensor as stated in [48–50] to damp the vibration of the end effector of AIA. A novel approach for active vibration damping of the TUDOR (3-Dof flexible link robot arm) using RGB-D sensor based on the eye-in-hand configuration is addressed by several articles [60–63]. The limitations such as frame rate and camera resolution are studied practically using TUDOR test rig. The end-effector oscillations of TUDOR system are suppressed using energy-based model free in conjunction with damping controller.

The RGB-D camera,[61] which is different from RGB sensor by providing per-pixel depth (D) values computed from a reflected pseudorandom-structured infrared light pattern. The authors compared six different visual oscillation sensing approaches on scenes, including sparse texture and poor geometrical profiles as well as static and dynamic contents, by utilizing the per-pixel depth measurements to reconstruct the 6D vector of the camera motion between two subsequent acquired images. The method involving the image Jacobian, the homography and the rigid transformations after back projection rely on a previously extracted set of point feature correspondences from subsequently acquired images. The problem of time-delay compensation for the TUDOR system has been studied in [62]. Fourier extrapolation, sinusoidal regression and autoregression, signal processing approaches to compensate for the sensor inherent delay are compared. TUDOR system is used under gravitational influence to catch multiple balls sequentially thrown by a human in [63]. The ball detection, tracking as well as the prediction of the ball intercept location is based on a wall-mounted Kinect RGB-D sensor. Varying payload and flexible link deformations are damped out using model free independent joint controller.

The application of the IBVS algorithm has been validated to a space manipulator for an eye-in-hand camera using a software simulation tool, and then by means of the experimental test bed in [64,65]. In their works and due to its simpler arrangements, the IBVS have been adopted to control three flexible links with eye-in-hand camera. An image processing algorithm is developed for adapting itself to different lighting conditions. However, in their papers only fixed targets are considered. Since the camera affected by the flexible vibration and visual distortion, an extended Kalman filter (EKF) is not only used for the estimate of the feature motion but also account the camera measurements in the case of camera failure. The usage of a camera system for navigation and flexible vibration control is analyzed in the work.

5.2. *Eye-to-hand configuration*

In the eye-to-hand configuration, the camera is fixed in the workspace and its continuously focusing on the robot end effector. In this case, the camera image is independent of the robot motion, the weight of the camera is not representing an additional payload to the system, and the auto focus feature is not necessary, in contrast to the eye-in-hand configuration. The main disadvantage here is the limitation of the workspace; the robot can be controlled by keeping it in the field of view during the visual servoing. The eye-to-hand high-speed camera configuration which available for visual servoing is used by [66,67], to identify the dynamic model of two-link flexible robot around a particular position. Using the identified model, a generalized predictive controller in the frequency domain, and $H\infty$ controller are implemented practically for validation of the model. The main disadvantage is the arm generally has to remain around particular position, which makes the model only appropriate for medical application. An advanced multiple-input and multiple-output control strategy is designed in [2] for high-speed visual servoing based on recomputing model after camera displacement, and the robustness due to a change in the working position is evaluated.

In [68], the results of ground-based experiments on the assembly of flexible space structures using the hardware developed under the self-assembling wireless autonomous reconfigurable modules (SWARM) program is presented. Two estimation systems are introduced for observing the dynamics of flexible beam using vision measurements. The Kalman filter is used to estimate the internal beam joint angles, while the steady state filter is used to estimate the angular position and angular velocity of the total beam deflection. Adaptive control is used to generate the control signal using the measurements and the model information. The SWARM program has successfully demonstrated the maneuvering and docking of a flexible beam in a 2D flat floor environment. In [69,70], they illustrated the problem related to state variable estimation of elastic ship-mounted crane using vision sensor data, the main goal of the work was to develop an approach to combine suitable measurement devices easy to realize with improved reliability. The task which be solved was estimations of the variable gain observer (based on vision measurements) with those of the variable gain observer (based on potentiometers) are combined. By realizing a multi-model approach the variable gain controller uses the variable gain observer's estimated states and the roll angle to generate the required damping to control the system to reduce the payload pendulations.

6. Summarized state of art

The main inherent problem regarding visual servoing are the limitations of vision sensor, long-time image processing, image resolution, and frame rate. Although relatively fast cameras and visual algorithms exist, the sampling rates of visual measurements are still lower than the frequency of positional encoders and joint angle sensors. In a flexible robotics context, the visual measurements are often needed to provide a feedback for control, or measurements to estimate the dynamic state variables of the system. In feedback control to attain controller stability, the sample rate needs to be high enough and the low sensor delay. The sensor delay of the visual measurements must be taken into account when estimating the state variables of the system for state feedback control. By combining the visual measurements with high frequency position information the control loop can be run with higher frequency to allow better stability and faster convergence. In addition, the sensor delay of the visual measurements must be taken into account when fusing the measurements. Especially eye-in-hand configuration requires precise synchronization of the traditional measurement and visual measurement. Otherwise, vision gives erroneous information while the end effector is in motion.

In addition to low sample rate and sensor delay the visual measurements are uncertain. The resolution of a camera is limited, image noise is present and motion blur adds error to the image. The dynamics and control of 3D flexible robot motion are more complicated when using a single measurement at each time instant as is it typical in visual servoing. More than one camera (scenario) can be used effectively in the 3D visual servoing of flexible robot system. The uncertainty in visual measurements can cause undesired oscillations and hinder the accuracy, by fusing multiple measurements together more accurate estimates of target motion can be made compared to a single image.

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Notes on contributor

M.T. Hussein was born in Al-Qadisiyah, Iraq, in 1983. He received his BSc, and MSc degrees in mechanical engineering from University of Babylon, Babylon, Iraq, in 2005, and 2008, respectively. He joined the Department of Mechanical Engineering, University of Babylon, in 2008. In 2014 he gained his Dr. Ing. degree in mechanical engineering from the University of Duisburg-Essen, Duisburg, Germany. Since October 2014, he earned a university lecturer position in Babylon University. His main areas of research interest are modeling and control of robotics, and flexible mechanical systems. Dr Hussein is a member of the Iraqi Engineers Union.

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