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Neural Network Vision-Based Visual Servoing And Navigation for KSU-IMR Mobile Robot Using Epipolar Geometry

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***Abstract*— Mobile robots visual control system does suffer from a number of issues, as due to speed and complexity. Complicated kinematics relations, in addition, the needed computational time to execute a task, are also some related issues. This manuscript highlights a mechanism through which to approximate an inter-related visual kinematics relations that are part of visual servo closed loop system through an Artificial Neural Networks (ANN) system for a mobile robot visual servoing. The methodology followed and being applied to KSU-IMR mobile robot project, is based on the concept of integration of Neural Networks with an Image Based Visual Servoing system. ANN have been fully employed here to learn and approximate relations that relate a target movements to the mobile robot movement (POWERROB,[1]), through a visual servo.**

Keywords-component; Visual Servoing; ANN; Epipolar Gemetry; KSU-IMR Robotics System.

I. INTRODUCTION

The manuscript is presenting a research frame work being done at King Saud University, KSA, and is related to an image-based visual servoing technique for driving a mobile robot to some desired mobile localities (set-point), which is specified through a desired image previously acquired by camera. Vision guided mobile robotics systems have been introduced by researchers worldwide. The main focus of VGM research directions are how to let a mobile robots navigate in an unstructured environment without collusions. Mobile robot localization and mapping, is considered as the process of simultaneously tracking the position of a mobile.

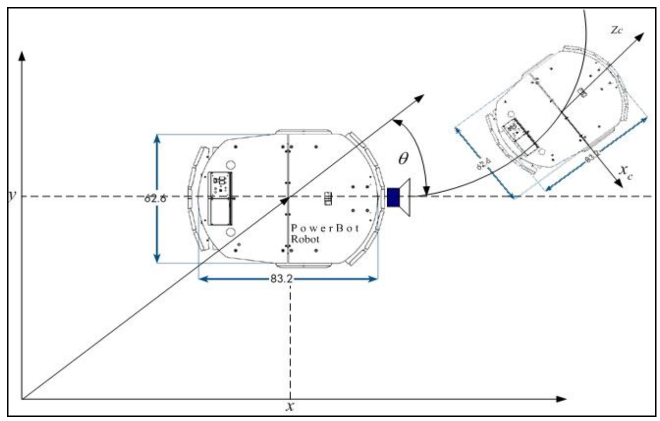

Figure 1. KSU-IMR mobile with unicycle kinematics carrying a camera.

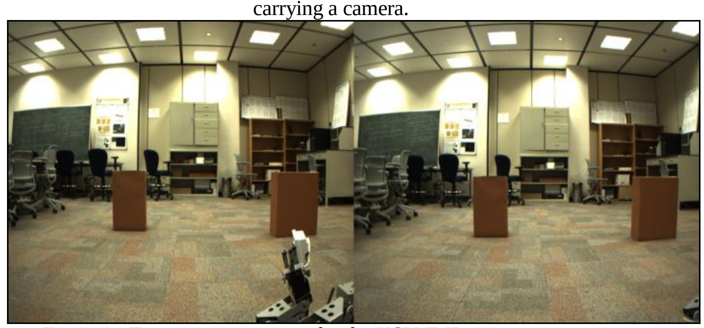

Figure 2. Target images as seen by the KSU-IMR two cameras system.

II. LITERATURE WORKS AND RELATED RESEARCH

A.) Background:

Lin et. al. in [2], stated that "minimizing the artificial potential energy of the mobile robot on a local 3D map plans a relay position and an approaching path. A self-

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learning controller using adaptive fuzzy systems is designed to manipulate the dynamic behavior of the mobile robot in tracking a planned path. Using Lagrange formalism, a mathematical model describing the autonomous mobile robot is derived for simulation study. Simulation and experimental results are presented", Lin et. al. [2].

Furthermore, Bai et. al. in [3], gave an introduction for an obstacle detection approach based on stereo vision. They stated, "The aim of the approach is to detect a real environment to allow a mobile robot to find a safe path even in complex scenarios. The novelty is represented in terms of the two-stage perception structure", Bai et. al [3]. Furthermore, Bais et. al. [4] have also introduced an augmented reality mobile robot based vision system. In their paper they, "introduce a tele-presence vision system for monitoring of a network based mobile robot", Bais et. al. [4].

"Development and integration of generic components for a teachable vision-based mobile robot", mentioned and introduced by Tomohiro et. al. [5]. In their paper, they presented, "a mobile robotic system for human assistance in navigation the robot navigates by receiving visual instructions from a human being and is able to replicate them autonomously. They describe three generic components defined as the HOST, the VISION, and the CONTROL components as well as their integration in the teachable mobile robot", Tomohiro et. al. [5].

Furthermore, a stereo vision-based autonomous mobile robot was further given by Changhan et. al. [6]. In their research, they reported "The proposed autonomous mobile robot consists of vision, decision, and moving systems. The vision system is based on the stereo technology, which needs correspondence between a set of identical points in the left and the right images", Changhan et. al. [6].

Stereo vision based self-localization of autonomous mobile robots was also introduced by Abdul et. al. [7]. They stated that, "The algorithm enables the robot to find its initial position and to verify its location during every movement. The global position of the robot is estimated using trilateration based techniques whenever distinct landmark features are extracted", Abdul et. al. [7].

Vision-equipped apelike robot based on the remote-brained approach was given by Masayuki et. al. [8]. "The key idea of the remote-brained approach is that of interfacing intelligent software systems with real robot bodies through wireless technology. In this framework the robot system can have powerful vision system in the brain environment. They have applied this approach toward formation of vision-based dynamic and intelligent behaviors of multi-limbed mobile robot", Masayuki et. al. [8].

Intelligent robot control using omnidirectional vision was introduced by Manoj et. al. [9]. Omnidirectional vision using a wide angle lens with a (2π) steradian field has been studied for image visualization and navigation for mobile robots. "The advantages of such a technique, is that, it can be obtained with the large field of view include instantaneous viewing which permits dynamic control and improved visualization. The significant geometric distortion can be corrected using image processing for either image viewing or target recognition", Manoj et. al. [9].

In [10], Bai et. al. have presented a two-stage perception structure. They mentioned "The approach synthesizes the statistical information of projections and depth discontinuities in the region of interest to characterize obstacles. The detection-confirmation structure is robust to various lighting conditions, effective to negative obstacles, free to specular reflection effect, and real-time response to the interference from dynamic obstacles. Experimental results verified the effectiveness, reliability and real-time performance of the proposed approach", Bai et. al. [10].

Hongshan et. al. [11] has reported the followings, "Firstly, four degrees of freedom of stereo platform with optimal baseline (34 cm), was designed for accomplishing visual tasks independently like pan, tilt and vergence of stereo camera. Secondly, step-motor drive scheme combined with closed loop servo controller was selected for multi-freedom controller in view of motor resolution requirement and system cost. Then, camera parameters controller was highlighted to enhance system adaptability by adjusting aperture, focus and zoom".

Additionally, in [12] Murray and Jennings have studied stereo vision based mapping and mobile robot navigation. They reported a use of an occupancy grid mapping, as "use of an occupancy grid mapping and potential field path planning techniques to form a robust cohesive robotic system for robotic mapping and navigation. In these projects, trinocular, which is described as three camera stereo vision system, was used". Researchers used some techniques to improve the quality of stereo vision results on a working system and several example implementation results are given in related references, [13].

B.) Manuscript Contributed Works:

This paper is focusing on the issue of mapping "visual kinematics mappings" for a "mobile robotics system",

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which is visually servoed using a trainable ANN. This is done for a mobile robotics system known as the "KSU-IMR". KSU-IMR is mobile robot platform dedicated for research purposes at King Saud University. The presented concept relies on approximating the complicated nonlinear visual mobile robot servo kinematics. Such kinematics are formulated due to mobile robot navigation, in addition to the inter-related kinematics of camera-mobile body Jacobian matrix. Here we are assuming the robot is to servo itself towards a scene features. The research is also presenting how a trained ANN can be utilized to learn few nonlinear relations governing a scene drift to mobile a mobile robot motion.

The research whole concept has been based on a and use of three fundamentals SIMULATION ENVIRONMENTS. FIRST, is the mobile robot motion and target visual kinematics. This done by using a MatLab Based ROBOT toolbox. SECOND, is also a use of MatLab Based Epipolar Geometry (two scenes geometry analysis) tools, for relating scenes during servoing. THIRD, is also the MatLab Based ANN toolbox. Results have indicated that, the proposed servoing methodology was able to produce a considerable accurate results for navigation towards a scene location via visual servoing. The employed robot used for such a study, is known as the POWERROB mobile robotics system [1]. Typical KSU-IMR robot kinematics are shown in Fig. (1).

III. Dual Scene Seen By A Mobile Vision (Epipolar Geometry Analysis)

To build a closed loop visual servo system, a loop is to be closed around the robotics mobile system with a camera. For an image geometry and associated moldings, are already known in literature. Fig. (3) illustrates two scenes geometry for two successive images of a camera representation. For analyzing closed loop visual kinematics, we shall employ a (Pinhole Camera Model) for capturing a scene features. For accurate modeling, details of a Pinhole camera model in terms of image plane locations (x^a, y^a), are thus expressed in terms $(X \quad Y \quad Z)$, as given by Equ. (1). In reference to Fig. (3), we can express image locations (x^a, y^a) as expressed in terms $(X \quad Y \quad Z)$:

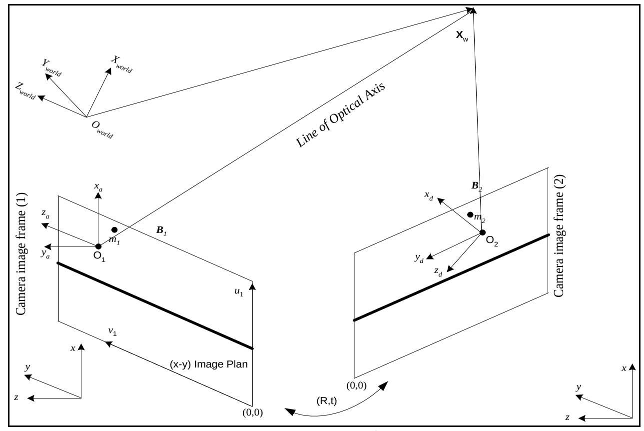

Figure 3. Epipolar geometry. A means for modeling and simulation a mobile robot-camera movements, for tracking a scene.

$$x^a = \phi^a\left(\frac{X}{Z}\right) \quad \cdots \quad y^a = \phi^a\left(\frac{Y}{Z}\right) \tag{1}$$

Together (x^a, y^a) are locations over an image plane. They are calculated by in terms of 3-D locations, i.e. the $(X \quad Y \quad Z)$, using Equ. (1). In case of "thin lenses", as the case for a Pinhole camera model, camera geometry are represented by: (Gian *et. al.* 2004), [14]:

$$\left(\frac{1}{\phi}\right) = \left(\left[\frac{1}{x^a}\right] - \left[\frac{1}{x}\right]\right) \tag{2}$$

In reference to (Gian *et. al.* 2004, [14]), we shall denote a coordinate of point $\{P\}$ in frame $\{B\}$. For translation case, this is given by:

$$ {}^BP = \left(\left\langle {}^AP\right\rangle + \left\langle {}^BO_A\right\rangle\right) \tag{3}$$

(3) In Equ. (3), $\{{}^BO_A\}$ is a coordinate of the origin $\{O_A\}$ of frame $\{A\}$ in a new coordinate system $\{B\}$. Rotations are thus expressed:

$$ {}^B_AR = \left({}^Bi_A \quad {}^Bj_A \quad {}^Bk_A\right) = \begin{pmatrix} {}^Ai_B^T \\ {}^Aj_B^T \\ {}^Ak_B^T \end{pmatrix} \tag{4}$$

In Equ. (4), $\{{}^Bi_A\}$ is a coordinate of $\{A\}$ viewed in an additional coordinate $\{B\}$. In case of rigid transformation we have:

$$ {}^BP = \left({}^B_AR\right)\left({}^AP\right)$$

$$ {}^BP = \left[\left({}^B_AR\,{}^AP\right) + \left({}^BO_A\right)\right] \tag{5}$$

For the case of more than one consecutive rigid transformations, i.e. form frames $\{A \rightarrow B \rightarrow C\}$, coordinate of point (P) in frame $\{C\}$ can then be expressed by:

$$ {}^BP = \left[{}^B_AR\left({}^B_AR\,{}^AP + {}^BO_A\right) + {}^CO_B\right]$$

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$$ {}^{B}P = \left({}^{C}_{B}R^{B}_{A}R^{A}P\right) + \left({}^{C}_{B}R^{A}O_{A} + {}^{C}O_{A}\right) \quad (6)$$

For the case $\kappa = (k\phi)$ and $\beta = (L\phi)$, then we identify these parameters $(\kappa, \beta, u_o, v_o)$ as intrinsic camera parameters, where they present an inner camera variables. Rewritten in a matrix notation, this is expressed as:

$$\begin{pmatrix} u \\ v \\ 1 \end{pmatrix} = \left(\frac{1}{\zeta^{C}}\right)\begin{pmatrix} \kappa & 0 & u_0 & 0 \\ 0 & \beta & v_0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}\begin{pmatrix} R & \Omega \\ O^{T} & 0 \end{pmatrix}\begin{pmatrix} \xi^{c} \\ \psi^{c} \\ \zeta^{c} \\ 1 \end{pmatrix} \quad (7)$$

Together $\{R\}$ and $\{\Omega\}$ extrinsic camera parameters, do represent coordinate transformation among camera coordinate system and world coordinate system. In particular, (u,v) point in camera image plan is evaluated via the following relation:

$$\begin{pmatrix} u \\ v \\ 1 \end{pmatrix} = \left[\left(\frac{1}{\zeta^{C}}\right) M\ p^{w}\right] \quad (8)$$

At this stage, we shall focus on the Epipolar Geometry. For an analysis of epipolar geometry, we need to look at two scenes taken from different camera postures. In Equ. (8), the M matrix is the CAMERA PROJECTION MATRIX. In reference to Fig. (3), we are having the case of two perspective views of the same scene taken from two separate viewpoints, as this illustrated in Fig. (3). Furthermore, we are assuming that both (m_1) and (m_2) are representing two separate points for two diverse views. Perspective projection through O_1 and O_2, of the same point $\{X_w\}$, for both image planes. Assuming $\{c_1, c_2\}$ are the optical centers of two scene, the projection γ_1 and γ_2 of one camera center O_1 and O_2 onto the image plane of the other camera frame Λ_2 (Λ_1) is the epipole geometry. It is also possible to express such an epipole geometry in homogeneous coordinates in terms of $\{\tilde{\gamma}_1, \tilde{\gamma}_2\}$:

$$\tilde{\gamma}_1 = \begin{pmatrix} E_{1x} & E_{1y} & 1 \end{pmatrix}^{T} \quad \& \quad \tilde{\gamma}_2 = \begin{pmatrix} E_{2x} & E_{2y} & 1 \end{pmatrix}^{T} \quad (9)$$

A unique of epipolar geometry parameter is the $(H) \in \Re^{\in 3\times 3}$ FUNDAMENTAL MATRIX. The (H) matrix conveys furthermost of the information about the relative position and orientation $\{t, R\}$ between the two different views. The (H) algebraically relates corresponding points in two images through "Epipolar Constraints". For the case of two views of an identical point $[X_w]$ in 3-D space. They are (i.e. the views) characterized their relative position and orientation (t, R) and the internal camera parameters. The (H) is evaluated in terms of β_1 and β_2, representing extrinsic camera parameters:

$$H = \left[\beta_2^{-T}(t)_x R \beta_1^{-1}\right] \quad (10)$$

The 3-D $[X_w]$ point is projected onto two image planes, to points (m_2) and (m_1). They do constitute a conjugate pair. Given a point (m_1) in left image plane, its conjugate point in the right image is constrained to lie on the epipolar line of (m_1). The line is considered as the projection through C_2 of optical ray of m_1. All epipolar lines in one image plane pass through an epipole point. This is the projection of conjugate optical center: $\tilde{E}_1 = \tilde{P}_2 \begin{pmatrix} c_1 \\ 1 \end{pmatrix}$

Parametric equation of epipolar line of $\tilde{m}_1$ gives $\tilde{m}_2^{T} = (\tilde{\gamma}_2 + \lambda P_2 P_1^{-1} \tilde{m}_1)$. In image coordinates this can be expressed as:

$$u = [m_2]_1 = \frac{[\tilde{e}_2]_1 + \lambda[\tilde{v}]_1}{[\tilde{e}_2]_3 + \lambda[\tilde{v}]_3} \quad (11)$$

$$v = [m_2]_2 = \frac{[\tilde{e}_2]_2 + \lambda[\tilde{v}]_2}{[\tilde{e}_2]_3 + \lambda[\tilde{v}]_3} \quad (12)$$

Here $\tilde{v} = P_2 P_2^{-1} \tilde{m}_1$ is a projection operator extracting the (i^{th}) component from a vector. c_1 is in the focal plane of right camera, right epipole is an infinity, and the epipolar lines form a bundle of parallel lines in the right image. Direction of each epipolar line is evaluated by derivative of parametric equations listed above with respect to (λ):

$$\left(\frac{du}{d\lambda}\right) = \frac{[\tilde{v}]_1[\tilde{e}_2]_3 - [\tilde{v}]_3[\tilde{e}_2]_1}{([\tilde{e}_2]_3 + \lambda[\tilde{v}]_3)^2} \quad (13)$$

$$\left(\frac{dv}{d\lambda}\right) = \frac{[\tilde{v}]_2[\tilde{e}_2]_3 - [\tilde{v}]_3[\tilde{e}_2]_2}{([\tilde{e}_2]_3 + \lambda[\tilde{v}]_3)^2} \quad (14)$$

(Top)

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(Down)

Figure 4. (Top) : The BUMBLEBEE, 8, 16, 24-bit digital data. (Down): Mobile robot PowerRob used for the experiments, equipped with dual camera system.

IV. A LEARNING BASED IMAGE-BASED MOBILE ROBOT VISUAL SERVO CONTROL

Having discussed the geometry associated with two different cameras views. Within the following section, we shall focus on Image-Based Visual Servo (IBVS) for a mobile robotic system. Here we are assuming the mobile uses locations of a target features on image planes (epipolar) for direct visual feedback. It is desired to keep the mobile body moves in such a way that camera's view changes from "initial" to a "final" view. The feature vector to change from current features $\{\phi_c\}$ to $\{\phi_d\}$. The features vector $\{\phi_c\}$, comprises "coordinates of vertices", or "areas" of the scene to be tracked. Implicit in $\{\phi_d\}$ is the mobile normal to, and centered over features of a scene, at a desired distance.

For a mobile robot system with a mounted camera, as in Fig. (4), viewpoint and features are functions of relative pose of the camera to the target, $({}^{c}\xi_{t})$. It is always found that, such a function is usually nonlinear and cross-coupled. The motion of the robot mobile body results in compound movements of numerous features. For instant, the mobile rotation (with camera onboard) causes features to "translate horizontally and vertically" over the image plane. This given by the following relationship:

$$\phi = f_{mobile}\left({}^{c}\xi_{t-features}\right) \tag{15}$$

Equ. (15) is to be linearized. Linearrization is to be made a nearby an operating point:

$$[\delta\phi] = \left({}^{f}J_{c}\right)\left({}^{c}x_{t}\right)\left[\delta\,{}^{c}x_{t}\right] \tag{16}$$

$$\left({}^{f}J_{6}\right)\left({}^{c}x_{t}\right) = \left(\frac{\partial\phi}{\partial^{c}x_{t}}\right) \tag{17}$$

In Equ. (17), $({}^{f}J_{c})$ is the features Jacobian, Gian et. al., [14]. Such a matrix is relating rate of change in mobile robot posture to rate of change in feature space. For the case the Jacobian is "square and non-singular matrix", this results in $({}^{f}J_{c})$ to be an invertible as given by:

$${}^{c}\dot{x}_{t} = \left({}^{f}J_{6}\left({}^{c}x_{t}\right)^{-1}\right)\dot{f}_{features} \tag{18}$$

from which a controller law is expressed by:

$$\dot{x}_{t}^{c} = \left(K_{p}\right)\left({}^{f}J_{6}\left({}^{c}x_{t}\right)^{-1}\right)\left(f(t)_{d} - f_{c}(t)\right) \tag{19}$$

will tend to servo the mobile robot body to specific desired feature vector. In Equ. (19), K_p matrix term the gain matrix, and (t) indicates a time varying quantity. The target posture rates in space is $({}^{c}\dot{x}_{t})$ is converted to mobile robot body rates. A Jacobian, ${}^{f}J_{6}({}^{c}x_{t})$ as derived from relative pose between the mobile robot and camera, $({}^{c}x_{t})$ is used for that purpose. In terms of features, both Tsai and Lenz, as in [15], have outlined a technique to compute the transformation (that involves Jacobian features), between a robot body and the camera frame. In turn, mobile speed rates may be converted to mobile speed rates using the robot Jacobian in space, as follows:

$$\dot{\theta}_{t} = {}^{t6}J_{\theta}^{-1}(\theta)^{t6}\,\dot{x}_{c} \tag{20}$$

In Equ. (20), $\dot{\theta}_{t}$ does represent the mobile robot joint space rate (wheels speeds). Therefore, a complete closed loop equation thus be given by:

$$\dot{\theta}_{t} = K^{t6}J_{\theta}^{-1}(\theta)^{t6}J_{\theta}^{f}J_{c}^{-1\,c}x_{t}\left(f(t)_{d} - f_{c}(t)\right) \tag{21}$$

An analytical expression of an "error function" is given by:

$$\varphi = \left(Z^{+}\varphi_{1} + \eta\left(I_{6} - Z^{+}Z\right)\frac{\partial\varphi_{2}}{\partial X}\right) \tag{22}$$

In Equ. (22), $\eta \in \Re^{+}$ and (Z^{+}) is a pseudo inverse of the matrix (Z), $Z \in \Re^{m\times n} = \Re(Z^{T}) = \Re(J_{1}^{T})$ and (J) is the Jacobian matrix of task function as $J = \left(\frac{\partial\varphi}{\partial X}\right)$. In terms of controller robustness, this closed-loop system is relatively robust. This is for the case of possible occurrence of image distortions and mobile robot parameter variations (for both kinematics and dynamics). In terms IBVS, it is always reported that, the significant problem is computing or estimating the feature Jacobian, where a variety of approaches have been used, Murray and Jennings, [12]. The proposed IBVS structure of Weiss, as was reported in M. Gian, et. al. [14], controls mobile robot joint movements directly using measured image features. Non-linearities include "mobile robot kinematics and dynamics", in addition nonlinearities due to the camera imaging system. Within the same context, due to posture dependency of ${}^{f}J_{\theta}^{-1}({}^{c}\theta)$, Lenz and Tsai [15] have used an adaptive control. However, within this study, changing relationship between mobile robot posture and the changes in image features will

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be learned during the mobile motion. This is to be done using a learning ANN, Fig. (6). The ANN architecture and training details of the used ANN will be furthermore discussed within the coming section.

V. SIMULATION MOBILE ROBOT VISUAL SERVOING

ANN visual servoing of mobile robotic system with a mounted camera and image processing systems are simulated here. This is more depicted in Fig. (5). During simulations, the task has been performed using PowerRob system and a camera that can provide position information of the target scene within the robot workplace. The mobile robot direct kinematics are given by through a set of equations of PowerRob robotics system. The mobile system are has been servoing to follow a scene of a target that is moving in a (3-D) space. The target scene was characterized by a number of features "marks". This will also be discussed and shown in Fig. (8). The target scene features will be mapped to the movement of scene in camera image plane through defined geometries. Hereafter, changes in features points, and the differential changes in mobile robot body, do constitute a data set used for training the ANN. The ANN architecture is hence shown in Fig. (6).

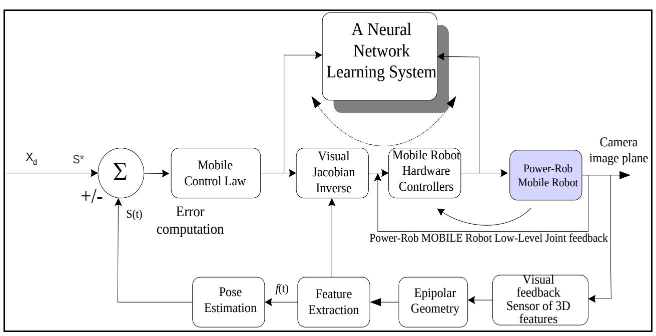

Figure 5. Gathering non-stationary object features.

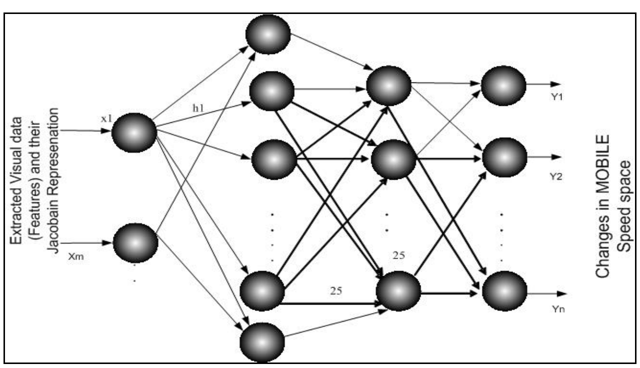

Figure 6. ANN used for learning the changes in visual features.

In this study, we have focused on the use of the "back-propagation algorithm" as the learning technique. Choice of the objective function is very important, as the function represents the design goals and decides what training algorithm can be taken. For this study frame work, a few basic cost functions have been investigated. Sum of squares error function was used as defined by Equ. (23):

$$E = \left(\frac{1}{NP}\right)\sum_{p=1}^{P}\sum_{i=1}^{N}\left(t_{pi} - y_{pi}\right)^2 \quad (23)$$

An derivation of a layered network with only two hidden layers. For this network there are (m) hidden units, and (n) output units. Output of the (j^{th}) hidden unit is obtained by first forming a weighted linear combination of the *i* input values, and adding a bias:

$$a_j = \left[\sum_{i=1}^{l}\left(w_{ji}^{(l)} x_i + w_{j0}^{(l)}\right)\right] \quad (24)$$

$$a_j = \sum_{i=0}^{l} w_{i=0}^{(l)} x_i \quad (25)$$

For each output (k) unit, first we get the linear combination of the output of the hidden units:

$$a_k = \sum_{j=1}^{m} w_{kj}^{(2)} h_j + w_{k0}^{(2)} \quad (26)$$

finally a (k) neuron output is given by:

$$y_k = g2\left(\sum_{j=0}^{m} w_{kj}^{(2)} g\left(\sum_{i=0}^{l} w_{ji}^{(l)} x_i\right)\right) \quad (27)$$

A.) *ANN TRAINING OF MOBILE MANEUVER*:

The employed ANN is shown in Fig. (6). The motivation is to drive the mobile robot. This will rather be simulated by Matlab, and equipped with a pin-hole camera, as simulated with Epipolar Geometry Toolbox. Details of such EGT, is found in Gian et. al. [14]. We need the mobile to servo from a starting scene toward a desired scene using only image data provided during the motion. In each case, the mobile was servoing with different object posture and a desired location in the working space. The EGT function to estimate the fundamental matrix (H), given (U_1) and (U_2), for both scenes in which (U_1) and (U_2) are defined in terms of scene 3-D (X, Y, Z) feature. Enormous training patterns have been gathered. Gathered patterns at various mobile "drifted postures gave an inspiration to a feasible size of learning ANN system. Four layers artificial neural system has been found a feasible architecture for that purpose. The ANN maps 24 (3×8 feature points) inputs characterizing target posture feature position and mobile body positions into differential changes in mobile posture. The ANN is presented with some mobile body motion in various directions. Once the ANN has learned with presented patterns, it is arranged to be used in the visual

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servo controller. The trained ANN was able to map nonlinear relations relating object movement to differentional changes in mobile 3-D posture. Once such large number of running and patterns, it was apparent that the learning ANN system was able to capture the stated nonlinear relations.

B.) Mobile Body Servoing After Training:

The execution phase begins primary while using the learned ANN system within the mobile robot dynamic controller. In refrecne to Fig. (5), the visual servoing dictates a use of visual features extraction block. That was achieved by the use of the epipolar toolbox. For assessing proposed visual servo algorithm, simulation of full mobile robot has been achieved using both (kinematics and dynamic) relations for the mobile robot. Robot toolbox, incorporating (Mobile Robots Simulations), was also used for that purpose. Results suggest high accuracy of identical results, indicating that a learned ANN was able to servo the mobile robot towards desired posture. Difference in error was recorded within a range of $(4{\times}10^{-6})$ for wheel motors movements. Fig. (7) shows the two mobile robot views via the two stereo vsiosn system, in addition to a 2-D maps of the environment under study. Fig. (8) also shows migration of the specific scene visual features, as observed over the camera image plan. As a validation of the ANN ability to servo the mobile towards a scene, in Fig. (9) we show that the trained ANN visual servo controller does approach zero level of movement, as for different training patterns for different mobile locations.

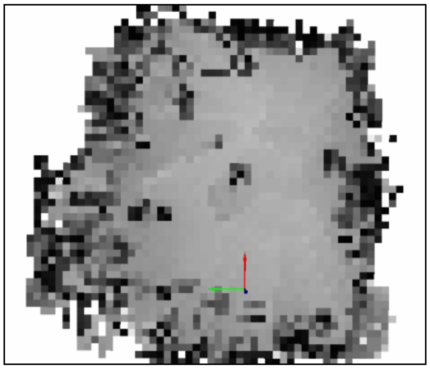

Figure 7. 2-D maps of the environment under study.

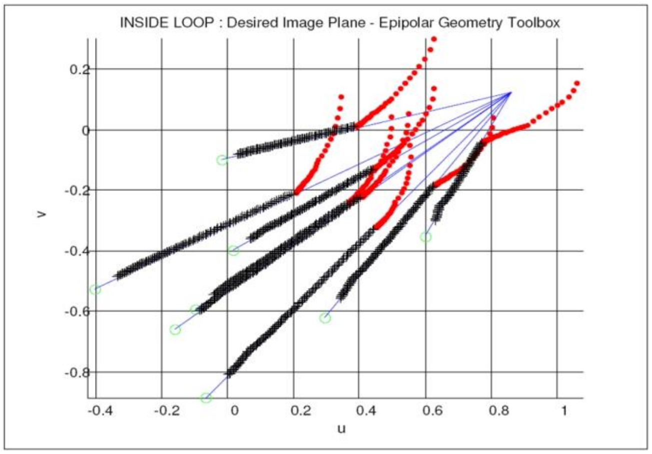

Figure 8. Mobile robot is servoing towards a scene. Here migration of scene visual features as seen over camera image.

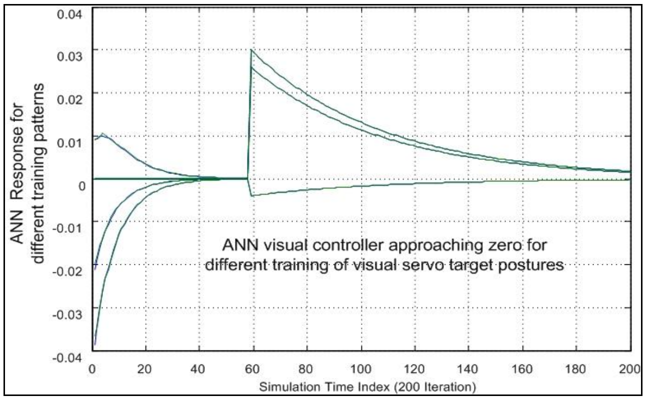

Figure 9. Running the ANN with closed loop controller. ANN output approaching zero.

VI. CONCLUSIONS

This manuscript has presented details of a project related towards visual servoing of a mobile (KSU-IMR) robotics system at KING SAUD UNIVERSITY. A novel IBVS strategy has been presented for visually servoing KSU-IMR mobile robot. The manuscript has also discussed the mechanism to learn the kinematics and feature-based Jacobian relations that describe the KSU-IMR robot. The concept introduced has been based on the employment of an ANN system trained to learn the mappings relating mobile drifts and visual kinematics and changes happening in visual scene. Changes in a loop visual Jocobain depends heavily on the mobile drifts from a locality, and on features associated with a scene under visual servo (to be tracked by the mobile robot). Results have shown that, such trained a ANN can be used to learn the complicated visual relations relating robot movements to an space movement. A key point is the use of multiple-view epipolar geometry during the first step in order to compensate the mobile body rotational error and align the current view to the desired one.

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