Literature survey for autonomous vehicles: Sensor fusion, computer vision, system identification and fault tolerance

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Abstract: Autonomous vehicle technologies are receiving great attention with increasing demands for autonomy for both civilian and military purposes. In previous work (Mohamed et al., 2016), the recent developments in autonomous vehicles in the fields of advanced control, perception and motion planning techniques is surveyed. In this paper, the state of research w.r.t. autonomous vehicles from different perspectives will be described. The capability to integrate data and knowledge from different sensors are essential. In addition, advanced perception techniques and the capability to locate obstacles and targets are necessary to properly operate autonomous systems. Moreover, achieve reliable levels of performance by determining the faults and enabling the system to operate with these faults in mind. Fault tolerance is required to analysing the measured input/output signals of the system. This paper will briefly survey the recent developments in the field of autonomous vehicles from the perspectives of sensor fusion, computer vision, system identification and fault tolerance.

Keywords: autonomous vehicles; sensor fusion; computer vision; system identification; fault tolerance.

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1 Introduction

Autonomous vehicles have become increasingly important assets in various civilian and military operations due to their capability for automatic navigation. These vehicles are able to operate and react to their environment without any outside controls. Autonomous vehicles offer numerous key advantages within the modern world. They can function during the daytime and at night when risky missions are involved (compared with manned ground vehicles).

In the last decade, significant innovations have taken place in the field of autonomous vehicles and for unmanned ground vehicles (UGVs) in particular. Autonomous vehicle navigation is especially difficult due to several obstacles including bad weather (Parhi and Singh, 2009). This can make it difficult to follow a pre-computed path precisely and also create uncertainty with the autonomous vehicle itself when there is insufficient knowledge of the surrounding environment due to limitations in sensor capabilities. As noted previously, this paper will deal with four major research fields in the study of autonomous vehicles: sensor fusion, computer vision, system identification and fault tolerance.

In general, the integration between data and knowledge, from several sources of sensors, is known as data fusion. Data fusion is the combination of data from various sensors and related information in order to enhance accuracy, which is not achievable when utilising a single sensor alone. The term data fusion is used when raw data is obtained directly via the sensors. Data fusion techniques have been widely applied to multisensory environments including camera Global Positioning Systems (GPS) and inertial measurement units (IMU). The aim here is to fuse and combine data using different sensors (Li et al., 2016). The goal of using data fusion, in multisensory environments, is to reduce the probability of any detectable errors and to obtain a higher rate of reliability by using data from multiple distributed sources.

Vision based autonomous navigation has mostly been enhanced for autonomous-based ground vehicles. The use of vision is very essential in solving problems involving autonomous navigation and localisation. In certain scenarios, in which the GPS is difficult to use, including bad weather or indoors where the signal is weak, the use of the vision system can help to overcome this problem and enable the autonomous vehicle to navigate successfully by analysing the visual features of the surrounding environment. In addition, the types of cameras that are used with autonomous vision based navigation strategies are light in weight and able to provide a clearer perception of the surrounding environment, in a single shot. Furthermore, we can detect nearby obstacles using the vision-based approach, especially utilising stereo-based cameras. Many vision-based detection autonomous systems have been developed over the last several years for this very purpose. They are able to provide real-time outputs as well as stable and reliable maps of the surrounding environment.

Developing an accurate dynamics model, for an autonomous type vehicle, can be challenging. For this reason, a system's identification approach can be introduced in order to solve such a problem (Sahu and Dash, 2011). System identification is the process of designing a mathematical model of a dynamic system by analysing the measured input and output signals of the system. System identification uses much of the same theorem as optimal estimation. However, rather than estimating the states of a system, system identification uses inputs and outputs to obtain a mathematical model that identifies the relationship between the input signals and the system response. In the case of autonomous ground vehicles, the process of system identification begins by identifying the specific input signals associated with each autonomous vehicle. Then, based on the input values entered, the vehicle can then perform maneuvers to suite the dynamics of the vehicle. In this instance, signals, given to the actuators, can be properly recorded and the actual vehicle parameters, related to vehicle acceleration such as yaw rate, lateral velocity, and steering wheel angle, and position, can also be recorded simultaneously. Based on this training data approach, an accurate model of vehicle dynamics can be properly identified.

Due to the increasing number of sensors and the underlying data fusion algorithms necessary, the risk of hardware and software faults increases in terms of sensor failures, actuators malfunctions, and processing failures (Aitouche and Ould-Bouamama, 2010). To overcome these issues and detect any faults, a fault tolerance control strategy needs to be developed to ensure more reliable performance outcomes with respect to autonomous systems. Fault tolerance control aims to prevent small faults from developing into serious failures and, in turn, increase plant reliability and reduce the risk of other hazards. Fault tolerant control (FTC) combines diagnosis with control methods in order to handle faults in a systemic way.

The next section will provide a survey of recent work on sensor fusion techniques applied to autonomous systems and to mobile robots. Several major sensors, including: vision cameras, IMU's and those associated with GPS will be discussed. Section 3 will provide a breakdown of different complex image processing algorithms using vision sensors and computer vision techniques that can better obtain the required data from the sensors. Section 4 will provide a breakdown of recent work associated with system identification techniques and their relationship to the dynamic models of the system. Section 5 will provide a breakdown of recent work conducted on fault tolerance control methods to achieve more reliable performance outcomes associated with modern autonomous systems. And lastly, the conclusion will be provided in Section 6.

2 Sensor fusion

Data fusion is the combination of data from various sensors and related information in order to enhance the accuracy that cannot be achieved by using a single sensor alone. This section, will summarise the state of the art sensor fusion methods and present findings from the most relevant studies. Most of the state estimation methods are based on the control theory and employ the laws of probability to compute a vector state from a vector measurement or a stream of vector measurements. The estimation methods considered in this paper will be:

1 maximum likelihood (ML)

2 Kalman filter methods

3 particle filter method.

2.1 ML method

The ML technique is an estimation method that is based on the probabilistic theory. Probabilistic estimation methods are appropriate when the state variable follows an unknown probability distribution (Brown et al., 1992). The main disadvantage of this method, in practice, is that it requires an analytical or empirical model of a particular sensor in order to ascertain prior distribution values and in computing the *likelihood function*. This method may also systematically underestimate the variance of the distribution, which can lead to data biases. However, the biases associated with the ML solution become less significant as the number N of data points increases and is equal to the true variance of the distribution that generates the data at the limit – $N \to \infty$.

Okello and Ristic (2003) developed a ML registration algorithm for spatial alignment of multiple, yet possibly dissimilar sensors in order to improve fusion performance. The purpose was to estimate and display the states of objects based on the received data collected via the distributed sensors. Still, the ML registration algorithm had its own limitations as follows:

1 it could estimate sensor biases only for a pair of sensors

2 the sensors had to be commensurate or completely alike.

In addition, this type of algorism could only handle a limited number of dissimilar sensors.

Chen et al. (2011) further developed the ML approach utilising joint image registration and fusion approaches. Moreover, the expectation maximisation algorithm was employed to solve any joint optimisation problems. Experiments were conducted using several types of sensory images for performance evaluation purposes, including visual imaging, IR thermal imaging, and hyper spectral imaging. The main advantage of using this approach was to attune the registration parameters such that an optimal fusion performance outcome could be achieved. Similarly, Kok and Schon (2016) developed the same approach for magnetometers and inertial sensors to estimate not only 3D orientations, but to also incorporate accurate calibration parameters.

2.2 The Kalman filter

The Kalman filter is the most popular estimation technique. It was originally proposed by Kalman (1960) and has been widely studied and applied since then. The Kalman filter estimates the state x of a discrete time process governed by the following space-time model:

$$x(k+1) = \Phi(k)x(k) + G(k)u(k) + w(k)$$

where $\Phi(k)$ is the state transition matrix, $G(k)$ is the input matrix transition, $u(k)$ is the input vector, $H(k)$ is the measurement matrix.

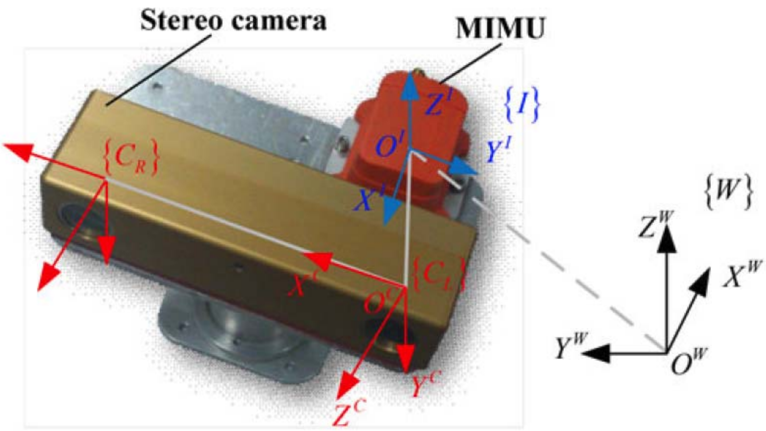
The Kalman filter is mainly employed to fuse low-level data. If the system could be described as a linear model and the error could be modeled as the Gaussian noise, then the recursive Kalman filter obtains optimal statistical estimations (Luo and Kay, 1992). However, other methods are required to address nonlinear dynamic models and nonlinear measurements. The modified Kalman filter, known as the extended Kalman filter (EKF), is the most optimal approach when implementing nonlinear recursive filters (Welch and Bishop (2001). Furthermore, the EKF is one of the most readily employed methods for fusing data in the case of applications utilising robotics. However, it has one major disadvantage; this being that the computations of the Jacobians can be extremely expensive. Some attempts have been made to reduce the computational costs, including applying linearisation, but this approach may introduce new errors in the filter and thus makes it more unstable.

Caron et al. (2006) developed a GPS/IMU multi-sensor fusion technique using Kalman filter estimation methods based on fuzzy subsets that could also be used with autonomous ground vehicles. The contextual variables were introduced to define the fuzzy validity domains of each sensor. The simulation was done using fusion data from the GPS and IMU of real vehicle tests. Due to the lack of credibility of the GPS signal, in some cases, and because of the drift of the INS, GPS/INS, the multi-sensor Kalman filter could be fed directly via the acceleration provided by the IMU. The author claimed that the multi-sensor filter was able to integrate a high number of sensors without changing its structure and the accompanying algorithm.

Li et al. (2015) proposed a hybrid intelligent multi-sensor positioning methodology for reliable vehicle navigation based on the Kalman filter in order to ascertain the filtering fusion. They introduced a hybrid intelligent, multi-sensor positioning technique fusing the data from low-cost sensors such as GPS, MEMS-based (SINS) and an electronic compass. It did act to enhance the performance over the integration scheme of these sensors. Moreover, an improved Kalman filter, alongside sequential measurement-update processing, was used to better ascertain the filtering fusion values.

Ryu et al. (2016) extended the Kalman filter and the unscented Kalman filter (UKF) to integrate the GPS with INS in order to reduce large errors associated with low-cost sensors and to estimate the accurate heading and positional data for future vehicle navigation. This method was tested using low cost sensors including GPS, electronic compass, and an inertial management unit. The obtained data was accurate, which shows that the EKF is better than the UKF when considering the time, it took to perform the overall process.

Figure 1 Fusing stereo camera and IMU for mobile vehicle navigation (see online version for colours)

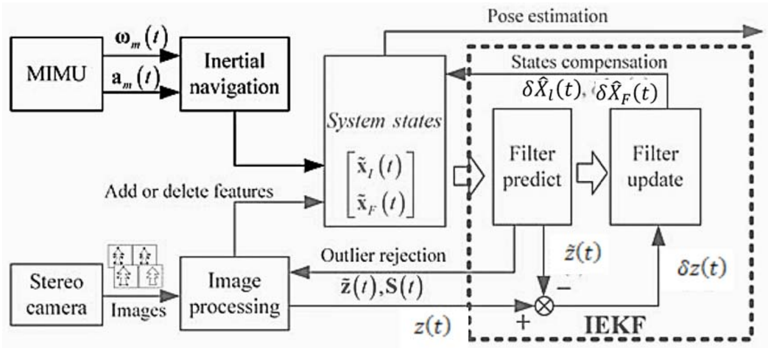


Source: Xian et al. (2015)

Mirzaei and Roumeliotis (2008) introduced the EKF in determining the 6-DOF transformation between a camera and an IMU, attached to a mobile robot. It combined the IMU data with visual observation's data from a camera under the assumption that the rigid transformation between the two sensors had already been ascertained. This method considered the time correlation of the IMU measurements by explicitly modelling them using an augmented-state EKF. In addition, this algorithm computed uncertainties in estimated quantities, or equivalently, the covariance.

Xian et al. (2015) introduced an integration of a stereo camera and a low-cost GPS to obtain the exact motion estimation for autonomous mobile vehicles navigation. They developed an algorithm using an iterative extended Kalman filter (IEKF) to estimate the motion within the overall system. In addition, this approach took advantage of the inertial sensor's fast response and the visual sensor's slow drift. Figure 1 shows the relationship between the stereo camera CL, CR and IMU reference frames, in which the stereo camera and the MIMU are rigidly attached. Figure 2, shows the integration flowchart between the camera and the IMU.

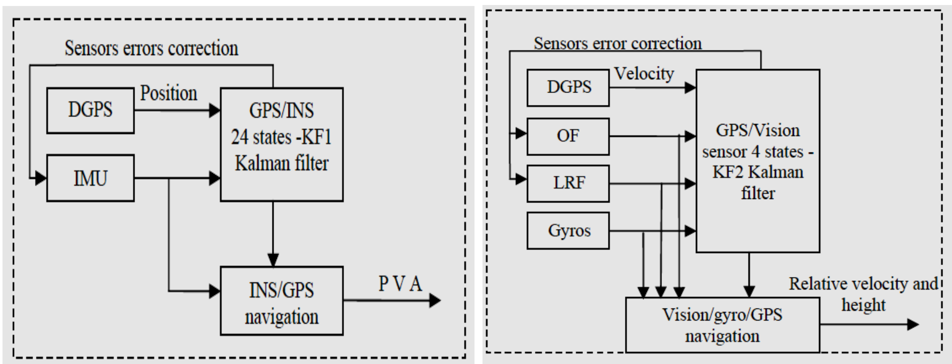
Figure 2 Flowchart of the tight integration system of the stereo camera and the MIMU



Source: Xian et al. (2015)

Wang et al. (2008) introduced an integrated GPS-INS-Vision navigation system for unmanned aerial vehicle navigation. In addition, A CCD camera and laser (range finder) based vision system were combined with inertial sensors in order to provide needed information on the vertical and horizontal movements of the UAV, relative to the ground. For this purpose, two Kalman filers were developed and operated separately in order to provide greater reliability with respect to navigational solutions. Furthermore, the obtained data from the GPS was used to update any error states associated with the two Kalman filters. The integrated GPS-INS-vision navigation system flow chart is shown in Figure 3, using two Kalman filters.

Figure 3 Integrated GPS/INS/vision system flow chart



(a) (b)

Source: Wang et al. (2008)

2.3 *Particle filter*

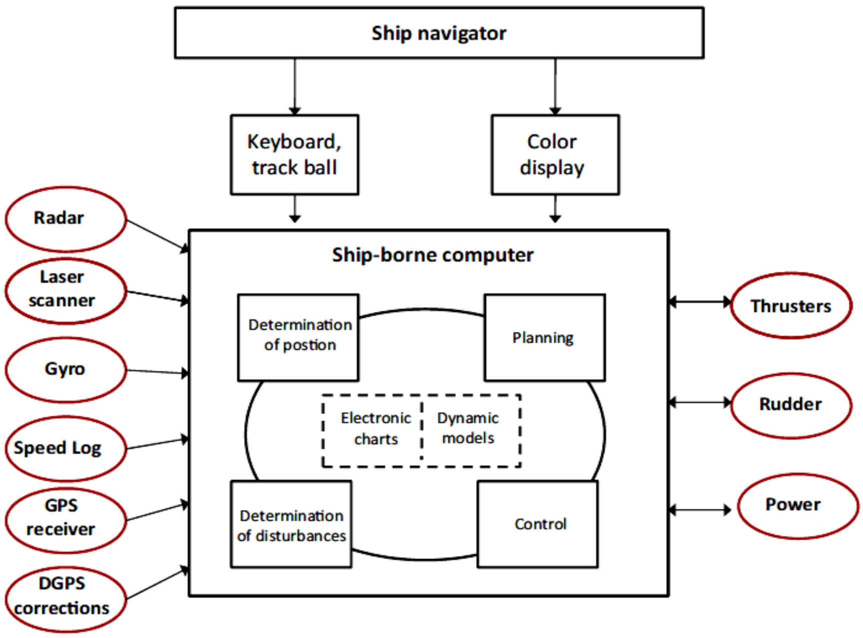
Particle filters are iterative implementations of the sequential Monte Carlo methods (Crisan and Doucet, 2002) to solve the filtering problem. This method builds upon the density function using several random samples called particles. These particles are increased over time vis-a-vie the integration of sampling and resampling steps. The sampling step is employed to discard some particles while also increasing the relevance of regions with a higher posterior probability. Additionally, during the filtering process, the particles that have the same state variables are employed and each particle has an associated weight that indicates the quality of the particle. Therefore, the estimation is the result of a weighted sum of all the particles. The standard particle filter algorithm has two phases:

1 the predicting phase

2 the updating phase.

In the predicting phase, each particle is modified according to the existing model and accounts for the sum of the random noise in order to simulate the noise effect. Then, during the updating phase, the weight of each particle is re-evaluated using the last available sensor observation, removing particles with lower weights.

Figure 4 Integrated navigation and dynamic positioning system with EKF and particle filtering (see online version for colours)



Source: Rigatos (2013)

Kurashiki et al. (2010) developed a self-localisation algorithm consisting of a two-dimensional laser range finder based on the particle filter for mobile robot navigation. Moreover, a robust control law and a path generation algorithm are combined with the localisation method to stabilise while driving on rougher terrain. The author claimed that the particle filter was applied instead of the EKF in order to handle sensory uncertainties when unexpected objects or obstacles appeared on the map.

Rigatos (2010) developed a sensor fusion (in motion control) method for mobile robots using an EKF as opposed to a particle filter. The estimated state vector of each mobile robot incorporating position measurements was used to ascertain feedback control laws and to obtain efficient trajectory tracking. The extended Kalman and particle filtering methods have been tested to deal with the problem of the estimation of the state vector of a mobile robot through the fusion of position measurements coming from odometrical and sonar sensors. Due to the poor outcomes associated with nonlinear functions, the EKF could be divergent. In order to deal with this problem, particle filtering was utilised.

Rigatos (2013) discussed the problem of dynamic ship positioning by developing a sensor fusion algorithm using both the Kalman filter and particle filter-based methods. Using the combination between the two filters (KF and PF) the research group was able to estimate the ship state vector by fusing the ship position and the heading measurements data that was obtained via the onboard sensors together with distance measurements data taken from sensors located along the coast. The obtained estimated state vector was used within the control loop in order to regulate the horizontal positioning and the direction the ship was heading in. Figure 4, illustrates the integrated navigation and the dynamic positioning system.

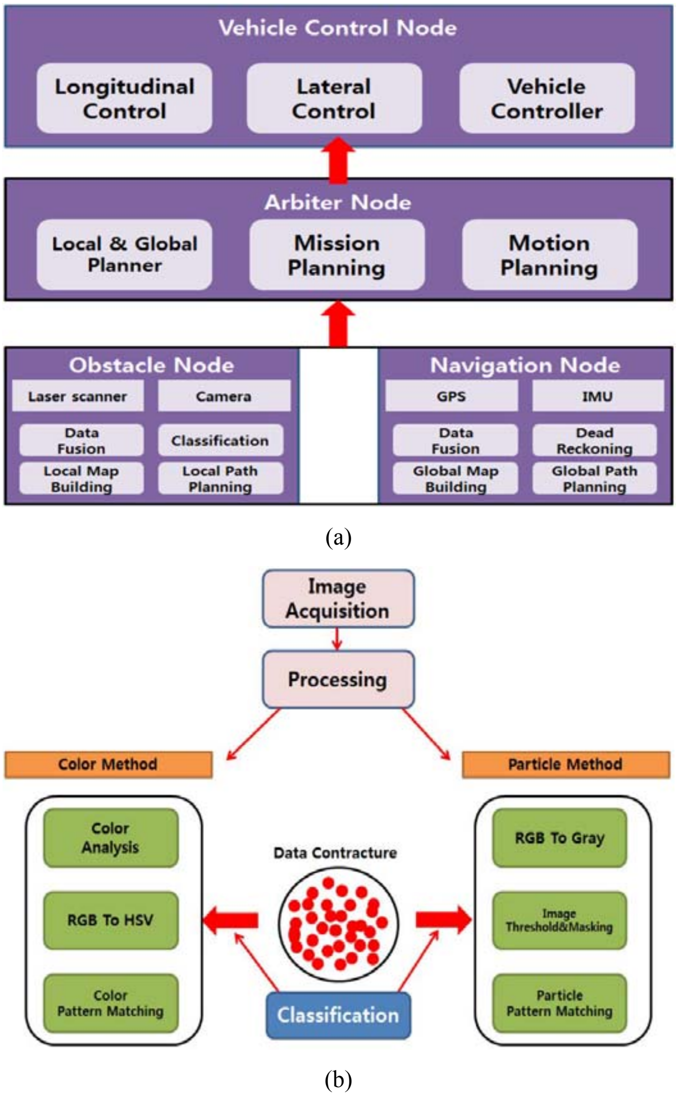
Hiremath et al. (2014) developed an autonomous navigation method for a robot equipped with a row-based LIDAR through a maze field using a particle filter based navigation algorithm (PF). The developed PF algorithm was used to estimate the robot-environment state of the system including a robot heading, lateral deviation, the distance between the rows of plants and the distance at the end of the rows. These estimated values were used to steer and direct the robot. The obtained results showed that the root mean squared error of the robot's heading and lateral deviations were equal to 2.4 degrees and 0.04 m, respectively.

3 Computer vision

This section reviews different complex image processing algorithms that are of necessity in developing UGVs which are more autonomous. UGVs should be equipped with the power to accurately process images directly on-board. In this way, we will ensure that UGVs can analyse and react to image acquisition in real-time and that they can avoid or track mission-based objects accordingly. In addition, a hardware platform is needed to perform image processing tasks on the UGV. This hardware platform could be a simple embedded processor such as the Raspberry PI or even a small computer like a laptop, depending on the processing power that is needed. However, they need to be lightweight, small and have adequate processing power at a low rate of consumption in order to work autonomously, for long stretches of time and without having to be re-charged.

Min et al. (2011) introduced an image recognition algorithm for UGVs using the information obtained through the camera. The developed algorithm could prevent accidents by measuring the distance between the vehicle itself and the vehicle in front of it. In addition, it was used to recognise lanes and prevent the vehicle from dropping out of its lane using measured distances between its wheels and the lane it was occupying. Additionally, by recognising road signs, the automated driving system was able to respond to these signs appropriately. Figures 5(a) and 5(b), shows the communicative design components of the UGV as well as the road sign recognition concept.

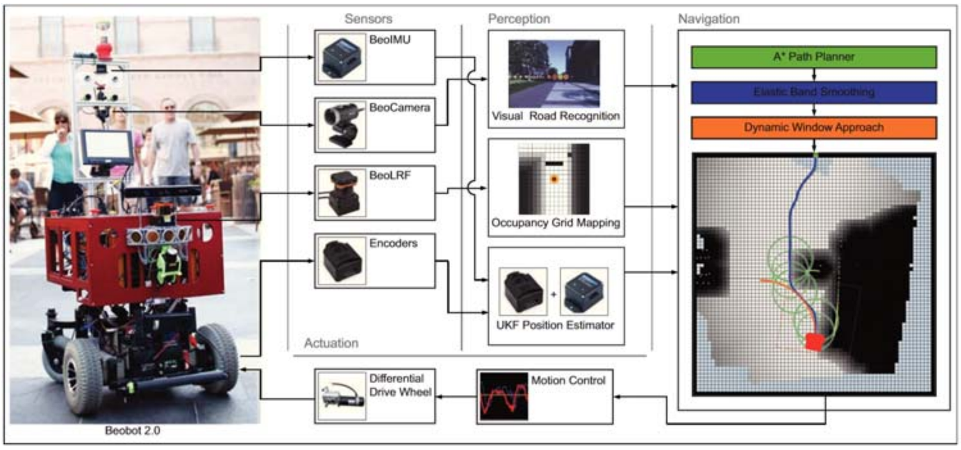
Figure 5 (a) Communicative design components of the UGV (b) The road sign recognition concept (see online version for colours)



Source: Min et al. (2011)

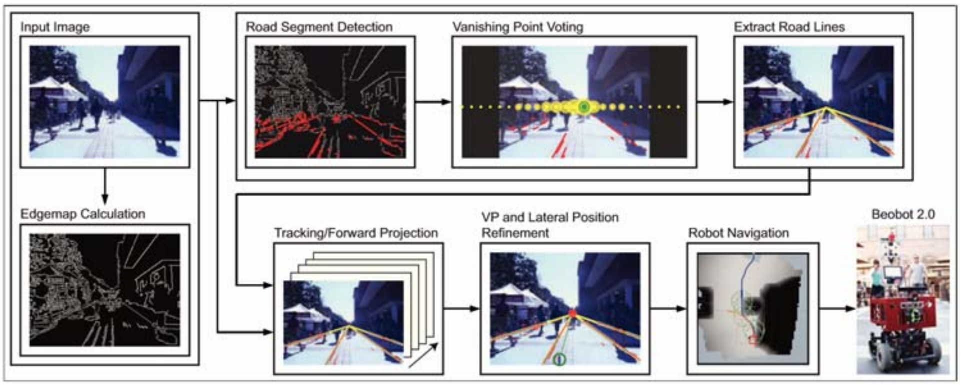
Siagian et al. (2013) developed a navigation system using a novel vision-based road recognition approach for a wheeled mobile robot. The chosen algorithm represents the road as a set of lines extrapolated from detected image contour segments. These lines enable the wheeled mobile robot to keep its proper heading by cantering the vanishing point (a point in the image plane that is the intersection of the projections of a set of parallel lines in space on to the picture plane) in its field of view, and, consequently, correcting the long-term drift from its original, lateral position. Additionally, the odometry and the visual road recognition system can be integrated into a grid-based, local map that best estimates the robot pose as well as its surroundings in order to generate a movement path. Figure 6, shows the autonomous navigation system fitted with sensors including IMU's and encoders to evaluate a robot's odometry. Further to this, a LRF is used to create a grid occupancy map while the camera is utilised to recognise the road and road conditions. Figure 7, shows the overall visual road recognition system, which was started by creating a canny edge map from a captured image. It can then evaluate the road by using the slower full recognition step and performing road segment detection, which can be used via road line extraction. The output includes both the road direction and the mobile robot lateral position (as part of the navigation system).

Figure 6 Beobot 2.0 autonomous navigation system (see online version for colours)



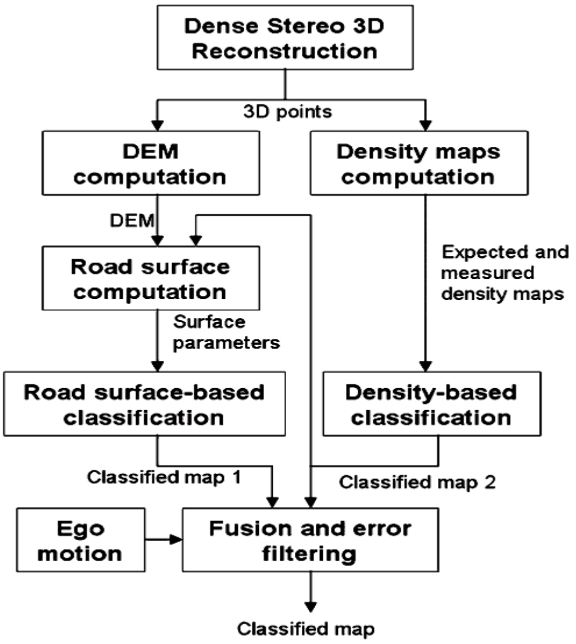
Source: Siagian et al. (2013)

Figure 7 Overall visual road recognition system (see online version for colours)

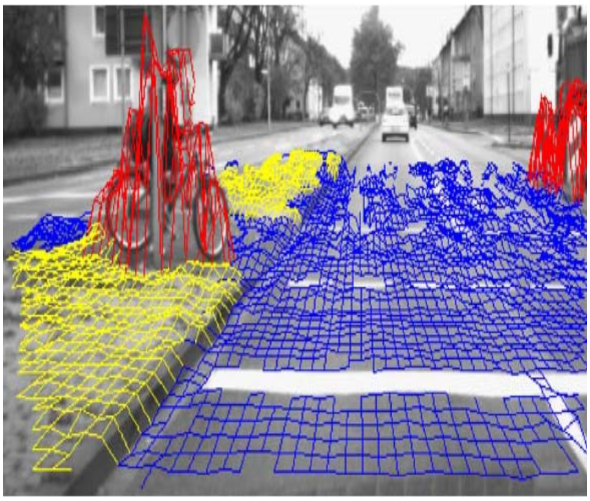


Source: Siagian et al. (2013)

Figure 8 (a) Overview of the proposed algorithm (b) Output of the algorithm (see online version for colours)



(a)



(b)

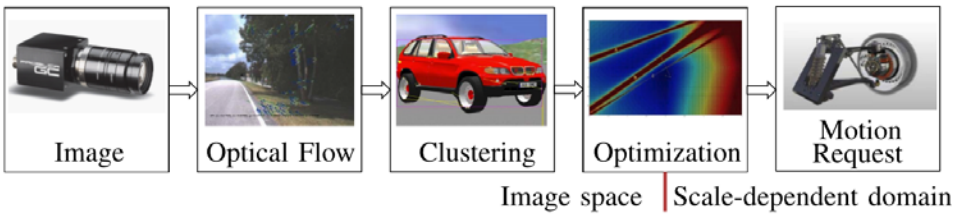
Notes: (Blue) road; (red) obstacles; (yellow) traffic isles.

Source: Danescu and Nedevschi (2014)

The digital elevation map (DEM) based approach, proposed by Oniga and Nedevschi (2010), is one of the major contributions to obstacle detection. A complete system for road surface estimation and obstacle detection were created through their work. The developed DEM and two density maps were computed from a set of 3D points in order to obtain a compact representation which involved explicit connectivity between adjacent 3D locations. Figure 8(a), provides an overview of the introduced algorithm. The road surface was fitted to a small patch, in front of the vehicle, using the RANSAC approach. Additionally, an obstacle detection algorithm was proposed based on the density of the 3D points, per DEM. The density-based algorithm used, for obstacle detection, was based on the density of these 3D points: each DEM cell was classified as an obstacle or road object using slope based threshold criteria. The average processing time, of 22 ms, was achieved utilising the entire algorithm. Figure 8(b) illustrates the final output results. Further to the work done by Oniga and Nedevschi (2010), another important method was proposed and put forth by Danescu and Nedevschi (2014). It consisted of applying the particle filter strategy in performing DEM tracking, which followed the dynamic DEM approach.

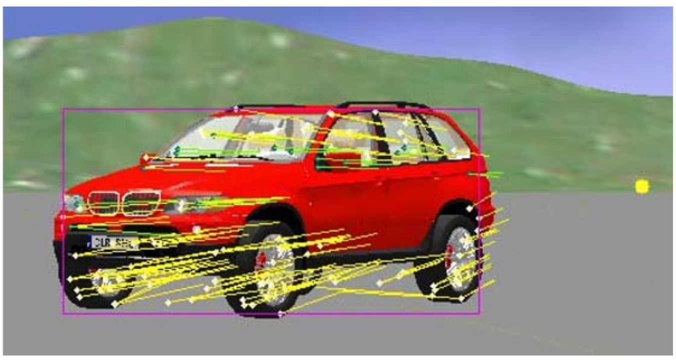
A reactive obstacle avoidance approach, based solely on the image data from a monocular camera stream, was proposed by Schaub et al. (2016). The established algorithm was able to identify potential collisions with dynamic obstacles by using two-stage clustering as well as an optical flow. Due to the direct coupling between the controls of the vehicle and the image motions, without a transformation into the Cartesian space, it was possible to explicitly consider and evade dynamic obstacles utilising image data from a monocular camera. Figure 9, summarises the necessary steps in moving from a monocular image sequence to a motion request. Figure 10 depicting a dynamic object identified by clustered optical flow vectors.

Figure 9 The underlying reactive perception to action chain (see online version for colours)



Source: Schaub et al. (2016)

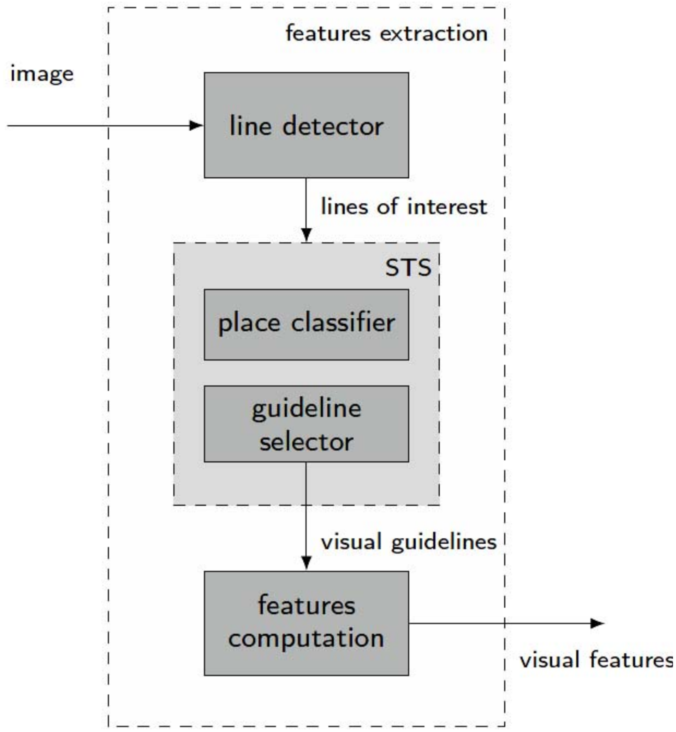
Figure 10 A dynamic object identified by clustered optical flow vectors (see online version for colours)



Source: Schaub et al. (2016)

Paolillo et al. (2016) proposed a visual control approach for humanoid indoor navigation. The aim was to have a robot follow a corridor by walking as close as possible to its centre and executing safe turns at corners and junctions using inputted, visual information. The algorithm utilised an image-based visual serving (IBVS) approach to generate navigation commands, which forced the humanoid to walk down the centre of the corridors using only visual information and without having any prior knowledge of its surrounding environment. The author claimed that the visual-based control law therein, proposed for the navigation of the humanoid robot down these corridors, was recorded in accordance with the corridor walls and their relative slopes. Figure 11, illustrates the whole process of featured extractions from the camera images block diagram.

Figure 11 Feature extraction block diagram



Source: Paolillo et al. (2016)

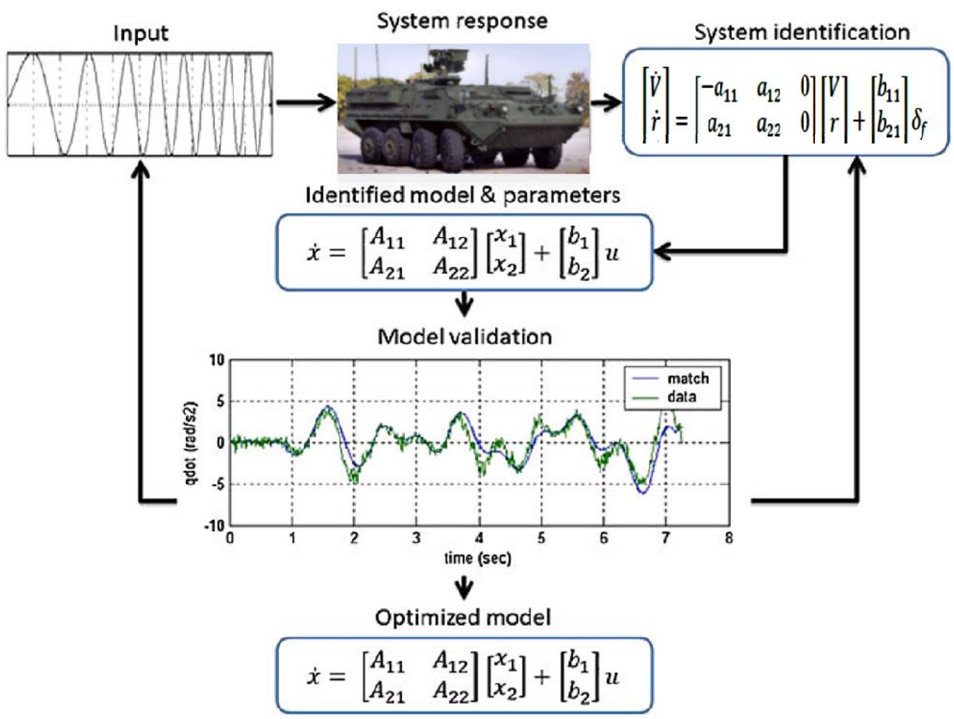
Chiang (2017) introduced an obstacle avoidance system using a humanoid robot as well. Here, the group utilised a webcam as its vision system and also incorporated the fuzzy logic approach. Based on the obtained image from the webcam, the navigation grid was then calculated. In order to reduce image noise, an erosion-dilation, and eight-connected component labelling approach were applied obtain the necessary images. Then the obstacle region was designed as a 'focus area' that each robot had to try and avoid. Further to this, the distance and direction from y to x were accurately calculated using filter processes. Then a proposed fuzzy logic algorithm was used to control the speed and the turning parameters for the motions associated with each robot and, consequently, allowed each robot to access any and all assigned routes. Furthermore, Mon and

Chung-Li (2013) also developed a vision-based intelligent obstacle avoidance algorithm for mobile robots using a single VGA camera. The captured images were processed by using the edge detection method. Additionally, an adaptive fuzzy logic, inference system (ANFIS) was also utilised. The detected horizontal edge number and the vertical edge number were inputted into the ANFIS to train the fuzzy rules and in order to control the right and left wheels of the mobile robot such that it could avoid certain obstacles.

4 System identification

This section provides a survey of system identification methods and applications. System identification is the methodology of determining a mathematical model of a dynamic system by analysing the measured input and output signals of the system. The process of system identification uses much of the same theory as with optimal estimation (Crassidis and Junkins, 2011) and control (Farrell and Polycarpou, 2006). However, instead of estimating the states of a system or observing the states necessary to drive a controller, system identification uses inputs and outputs to develop its model – describing the relationship between the input signals of a particular system and this system's output or response.

Figure 12 Overview of the system identification process (see online version for colours)

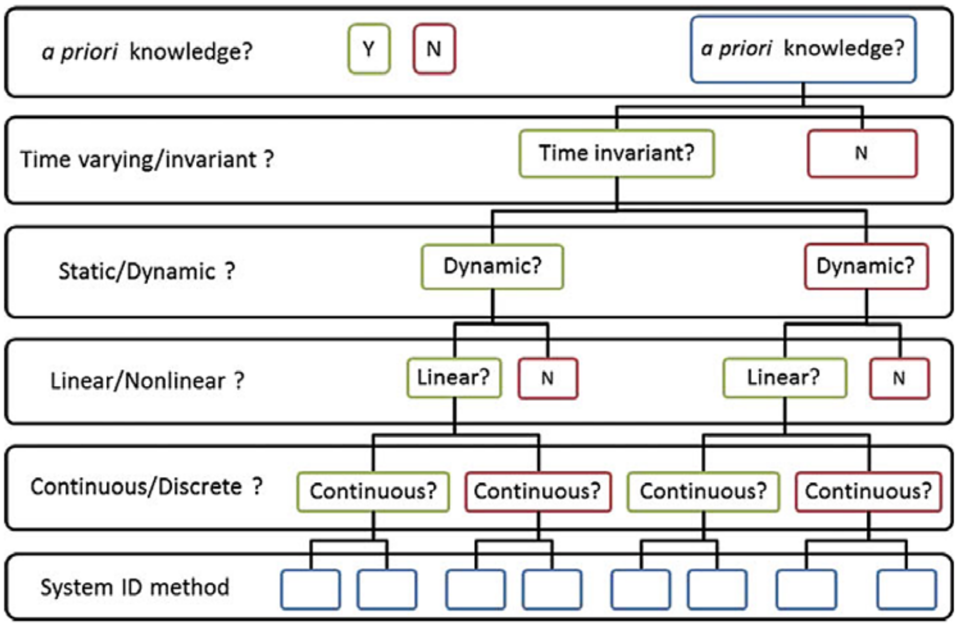


The process of system identification is summarised in Figure 12. There are five main elements associated with system identification as follows:

1 input signals
2 collected data
3 a section of the model structure
4 a section of the system identification method
5 optimisation of the model using system identification methods, a model structure and test data.

The selection of the system identification method is mainly dependent upon the application used and dynamic elements of the system. Figure 13, shows *the decision tree* for one particular system identification method. The decision tree asks specific questions about the dynamics of a system which, when answered, leads to the proper set of system identification methods.

Figure 13 System identification method decision tree (see online version for colours)



Source: Hoffer et al. (2014)

Nourizadeh et al. (2015) developed a time discrete model to describe the motion of wheeled mobile robots using these system identification techniques. In this study, the author utilised both auto regression moving average exogenous input (ARMAX) and nonlinear ARMAX (NARMAX) techniques. The author claimed that the designed controller, used with the ARMAX model, applied nonlinear dynamics associated with each wheeled mobile robot in a wide range of variations. Additionally, there were many advantages to using this method in that this model did not depend on the platform of the wheeled mobile robot; in other words, the model parameters could be estimated using recursive algorithms, including recursive least square (RLS). Specifically, this model had the ability to adapt itself to any changes that might be made to each specific mobile robot. The results show that the ARMAX model could achieve the same performance outcomes as the NARMAX model; however, the ARMAX model was simpler to design and required less computational time than did the NARMAX model.

Aras et al. (2013) developed and modelled a low cost underwater remotely operated vehicle (ROV) for depth control using the system identification technique to maintain its desired position. In order to apply the system identification technique, the input and output signals from the system were acquired first, then the system identification toolbox in MATLAB was applied to generate the model for the ROV. Consequently, the model of the ROV was tested in order to design the necessary controller.

A system identification approach, based on the prediction error method for a large-scale unmanned helicopter, was also carried out by Hashimoto et al. (2000). The helicopter's altitude was closely monitored permitting further experimentation during flight simulations. Using measured input-output data, the system identification method was first applied to the helicopter as a single-input-single-output (SISO) system, and then later applied as a multi-input-multi-output (MIMO) system. This was done in order to derive a mathematical model for the helicopter.

Karras et al. (2013) also designed an online identification system for autonomous underwater vehicles by estimating the dynamic parameters of the vehicle based on a global derivative free optimisation algorithm. The developed identification system consisted of the following three modules:

1 System excitation module: this module sent excitation inputs to the autonomous vehicle.

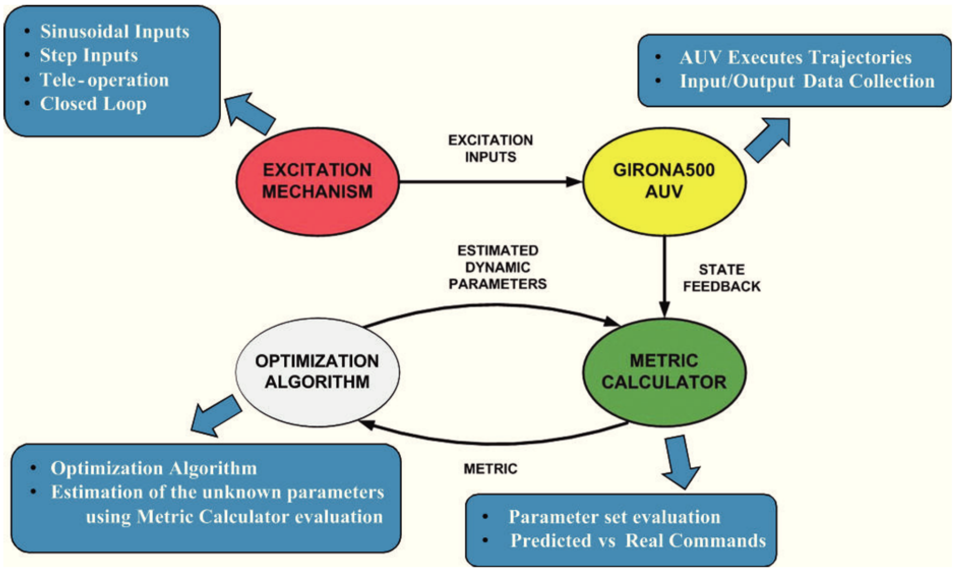
2 Optimisation algorithm module: this module calculated a candidate parameter vector that fed to the third module, which was called the metric calculator module.

3 Metric calculator module: this module evaluated the received candidate parameter vector from the optimisation algorithm module, using a metric based approach while also calculating the residuals of the actual and the predicted commands.

The authors claimed that the proposed algorithm was really a global algorithm, and unlike the UKF and the EKF, it did not depend on initialisation nor did it require the designer to pinpoint a good starting point. Figure 14, illustrates this online identification scheme.

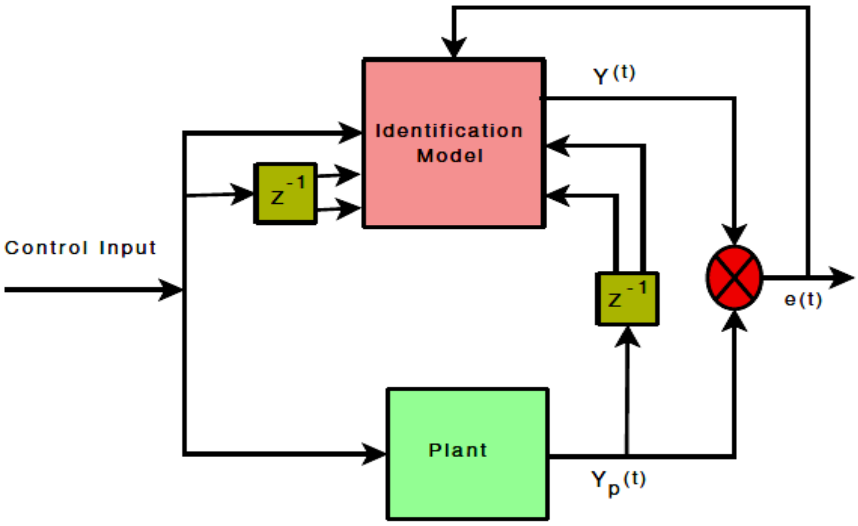
Eng et al. (2016) also developed an online system identification method, for autonomous underwater vehicle dynamic, vis-a-vie in-field experiments. The introduced identification process has two stages: the training stage and the validation stage. First, in the training stage, the unknown parameters are estimated using a state variable filter and a recursive least square (SVF-RLS) estimator. Second, in the validation stage, the prediction capability of the developed model is examined using a new dataset. According to the validation results, the identified model satisfied 78% to 92% of the o/p variation. A comparison between the SVF-RLS estimator and the conventional identification method revealed that the proposed SVF-RLS estimator was better in terms of prediction accuracy, computational costs and less training time.

Figure 14 Online identification scheme (see online version for colours)



Source: Karras et al. (2013)

Figure 15 Series-parallel model for NN identification (see online version for colours)

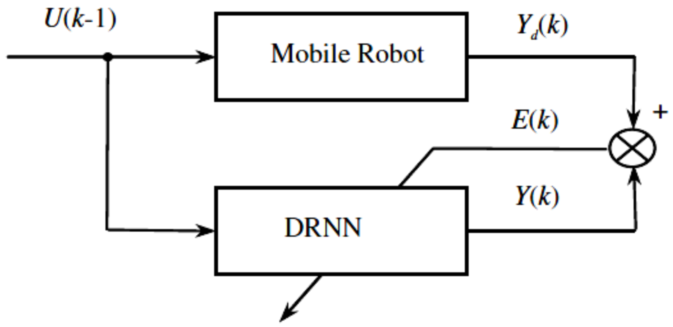


Source: Samal et al. (2008)

An offline and online neural network identification approach, in order to model the dynamics of an autonomous miniature Eagle helicopter, was introduced by Samal et al. (2008). The identification was carried out for both the coupled and decoupled dynamics of the helicopter via flight test data. The artificial neural network based, black-box method was used to model UAV dynamics and considered the interaction between all the inputs and outputs of a (MIMO) system. Figure 15, illustrates the series-parallel model for neural network identification. The predicted responses from these NN models, and the actual responses of the Eagle helicopter, were compared. The comparative results show that the offline model performed better when compared to the online model. The author claimed that the additional training time, and bigger batch size available for offline training, resulted in considerably better performance.

Jian'an et al. (2005) developed a kinematic model identification algorithm, of an autonomous mobile robot, using a dynamical recurrent neural network. By analysing the structure and the training algorithm of dynamical recurrent neural networks, the kinematic forward model identification of the autonomous mobile robot was realised. Experiments on AS-R mobile robots revealed that the dynamical recurrent neural network was capable of identifying the robot's kinematic model accurately. The block diagram, of the mobile robot kinematic model identification method, is shown in Figure 16.

Figure 16 Block diagram of kinematic model identification



Source: Jian'an et al. (2005)

Azmi et al. (2017) introduced modelling and control of remotely underwater vehicle using system identification technique. The ROV input/output signals of the system is measured, recorded and analysed to infer the model of ROV. Additionally, a MATLAB system identification toolbox is used to generate the ROV model. Based on the obtained ROV model it was used to developed a depth control system using PD controller.

5 Fault tolerance

This section provides a survey of a fault tolerant control (FTC) strategy that is required to achieve more reliable performance outcomes utilising modern autonomous systems. Faults are malfunctions of various elements within a technical system. The objective of FTC is to automatically detect error signals if there is a fault anywhere within the system and to maintain system stability and an acceptable performance level even when specific faults are present. FTC can be classified into two types: both passive and active FTC. Passive fault tolerant control can tolerate a predefined set of faults by using a specially-designed fixed controller while active fault tolerant control relies on fault detection and a diagnosis (FDD) process to monitor system performance. The latter can also detect and identify faults in the system and reconfigure the controller online and in real-time (Zhang and Jiang, 2008; Ducard, 2009; Benosman, 2009). The fault tolerant control system should be able to investigate the following issues:

1 Fast response time to failure, which means that failures must be detected before system performance is degraded to an undesirable level.

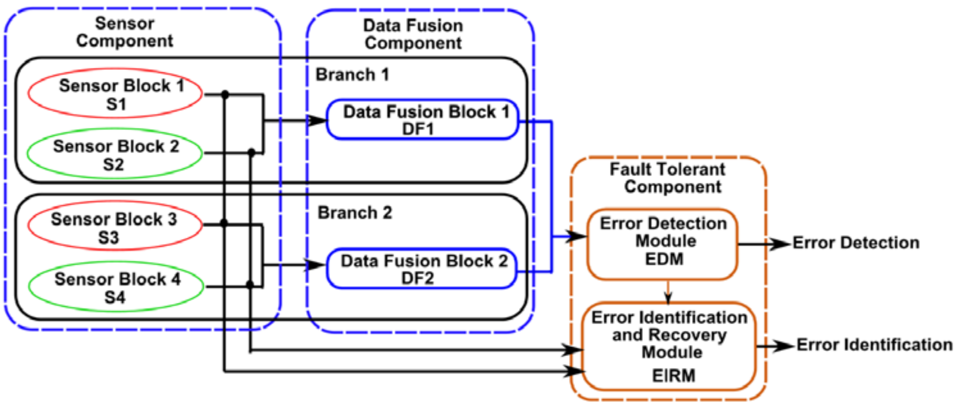
2 Graceful degradation of performance which requires that the system be maintained at the highest level of performance possible given the functional state of the hardware.

3 Access to all reliable resources – meaning that the system should reincorporate the use of repaired components.

4 Fault coverage requiring that the FTC system have the ability to handle as more failures as possible.

Bader et al. (2017) introduced an approach for tolerating faults using multi-sensor data fusion. The developed approach was based on the more traditional method of duplication comparison, which offers detecting and diagnosing faults in a data fusion mechanism. Fault tolerance is implemented principally via error detection and system recovery. Error detection aims to detect the erroneous state of the system before errors are propagated and thus cause system failures. A system can recover from this fault state by allowing an error-free state to be substituted in place of an erroneous state. Figure 17 illustrates the architecture for fault tolerance using multi-sensory perception and duplication-comparison.

Figure 17 Duplication-comparison architecture for fault tolerance in multi-sensor perception (see online version for colours)



Source: Rigatos (2010)

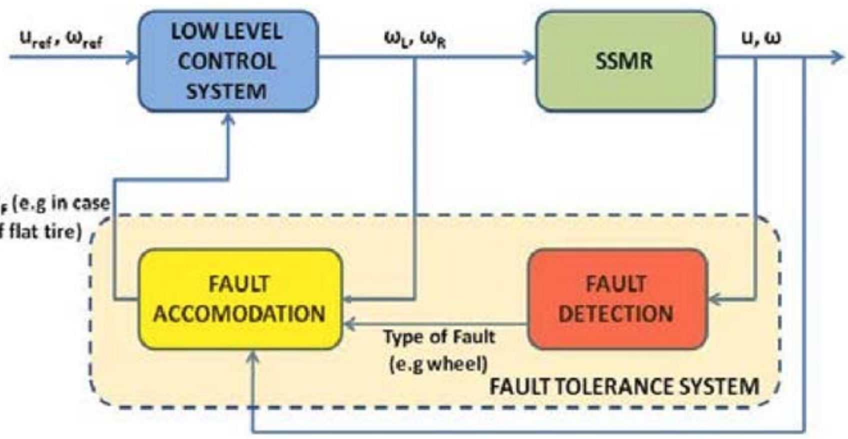
A model based fault diagnosis, for a four-wheel skid steering mobile robot, was carried out by Fourlas et al. (2015). The aim of this work was to detect faults, as early as possible, and recalculate command inputs in order to achieve fault tolerance. This offered a feasible solution to the residual generation of nonlinear systems. The fault diagnosis procedure was accomplished using a structural analysis technique. The fault tolerance was performed based on a RLS approximation. Figure 18 shows the overall structure of the proposed fault tolerant mechanism. It consists of two parts:

1 the fault detection module which accepts, as inputs, the measurement of the linear and angular velocity of the SSMR and further decides the appropriate type of fault to use according to the detection algorithm

2 the fault accommodation module, which accepts, as inputs, the type of fault required as well as the measurement of the linear and angular velocity.

It can also recalculate according to the command inputs used in order to compensate for any faults.

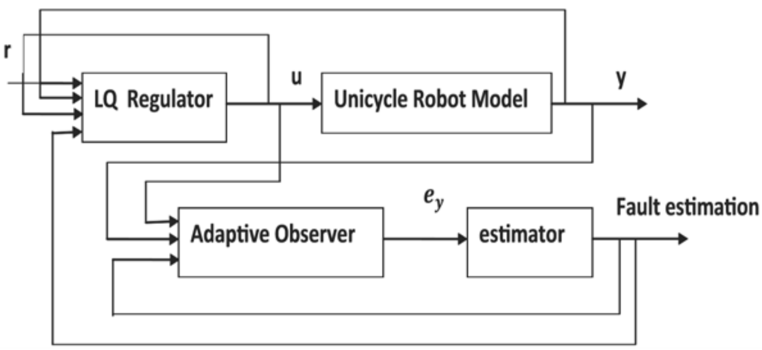
Figure 18 Fault tolerance system architecture (see online version for colours)



Source: Rigatos (2013)

Vlantis et al. (2016) introduced a fault tolerant control system for an omni-directional mobile platform using four mechanised wheels moving within a flat and constrained workspace along with a number of static-based obstacles. The authors defined the fault as the unactuated wheel, being exposed to friction, along this flat surface. Additionally, conventional and dipolar Navigation Functions were combined using adaptive control techniques to deal with the parametric uncertainty associated with the robot and its dynamics.

Figure 19 Fault tolerant control concept



Source: Schaub et al. (2016)

Olfa et al. (2015) designed a reconfigurable linear quadratic (LQ), state-feedback control tolerant to actuator fault. The idea of this approach was developed offline; a linear time-invariant controller using optimal LQ technique was used in reaching an optimisation goal. In this way, the developed technique allows mobile robots to autonomously detect, identify and rectify faults due to any actuator failures. Figure 19 illustrates a fault-tolerant controller designed to compensate for faults using a fast-adaptive fault estimation algorithm. This would guarantee the stability and reliability of the control systems utilised.

A new model-based fault tolerant, kinematic/torque control law was carried out by Thumati et al. (2012) using a *back-stepping* approach for leader-follower mobile robots, in a formation. The proposed control law was developed for leader and follower mobile robots in the case where no faults existed. An online model-based fault tolerant approach was introduced in the presence of a fault; this fault could be changed depending upon the nature and surroundings of the mobile robot. This fault was dealt with by adding another term into the control law; this new term would be a function of the fault dynamics, which could then be recovered using a neural network. The fault tolerant control law was verifiable based upon the Lyapunov theory.

Axenie (2010) introduced a real-time, distributed control application using fault tolerance capabilities for differential wheeled mobile robots. The fault tolerant control was based on the EKF that was utilised to estimate the current position of the mobile robot.

Additionally, any faults which occurred within the system, and in order to discriminate between them, the authors used a method based on residual computation and statistical analysis. The fault tolerant module consisted of three submodules as follows:

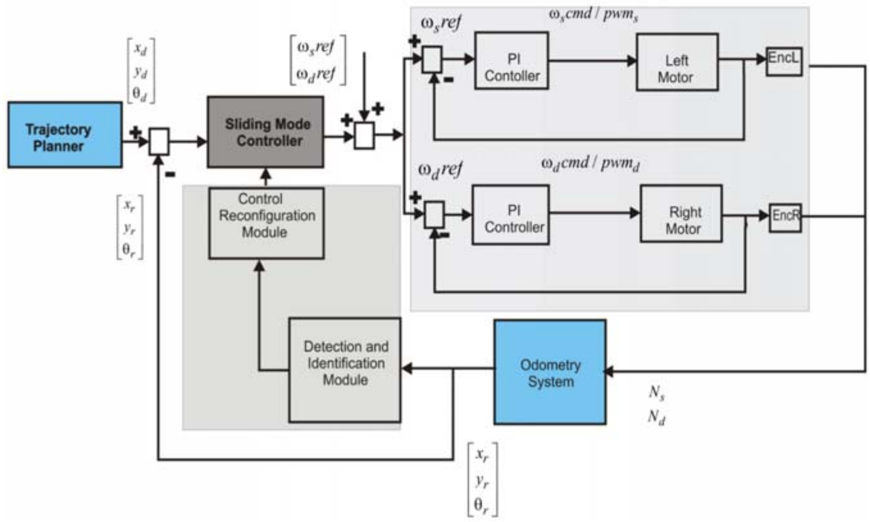
1 a fault detection submodule
2 a fault identification sub-module
3 a control reconfiguration submodule.

The complete architecture, of the mobile robot control system, is illustrated in Figure 20.

Dixon et al. (2001) also developed kinematics and dynamic models, of a wheeled mobile robot, in the presence of faults such that, any change in the wheel radius (e.g., deformation, broken spoke, flat tire) or general kinematics, could lead to disturbances in the model including slipping or skidding faults. Utilising the mobile robot models, the authors employed a torque filtering technique to develop a prediction error based fault detection residual. The fault detection residual was based on a prediction error which was the difference between the filtered torque signal and an estimate of the filtered torque. The structure of the prediction error allowed for fault detection despite parametric uncertainty in the mobile robot model.

Bhat et al. (2017) developed a software based fault tolerance algorithm that utilise task-level hot and cold standbys to tolerate fail-stop processor and task failures. The main advantage of using standbys is maximal when a task and any of its standbys obey the placement constraint of not being co-located on the same processor. Additionally, a task allocation algorithm is introduced for the first time to our knowledge, leverages the run-time attributes of cold standbys. Also, the developed software fault-tolerance framework is implemented in AUTOSAR, an automotive industry standard.

Figure 20 Control system architecture (see online version for colours)



Source: Sahu and Dash (2011)

6 Conclusions

This paper has provided a critical survey of the state of the recent developments in the field of autonomous vehicles from the perspectives of sensor fusion, computer vision, system identification and fault tolerance. Additionally, the survey has outlined the practical issues and technical challenges associated with the development of such approaches as they relate to autonomous vehicles.

Autonomous vehicles have many potential applications and the demand for them is ever increasing. The research put forth upon these vehicles has drawn interest among many researchers and organisations, in relation to both civilian and military applications. In fact, autonomous vehicles are already being used in some military operations including inspection, surveillance, and rescue operations.

Based on the extensive literature review presented in this paper, the selection of the sensor fusion estimation technique often depends upon the type of problem that exists in addition to established assumptions made for each technique utilised. Most of the state estimation methods that were used for sensor fusion were based on the control theory and the laws associated with probability. Many autonomous systems use cameras as the main sensor and vision has become one of the cheapest, promising yet challenging methodological approach when it comes to autonomous vehicles in a variety of different environments. Computer vision techniques have been applied in almost all environmental settings and among a large variety of mobile robots (ground, air, and underwater robots). Future planning to improve the positioning data for the multi-wheeled combat vehicle by developed a hybrid positioning technique for GPS/INS Kalman filter using both loosely coupled and tightly coupled integration for GPS/INS.

Undeniably, increased numbers of sensors can lead to some faults occurring due to hardware or software malfunctions. These faults are difficult to accurately predict over time. Thus, fault tolerance controls can be utilised in order to achieve more reliable performance outcomes among numerous autonomous systems. Clearly, fault tolerance control's purpose is to prevent simple faults from developing into serious failure; thus, not only increasing system reliability, but in helping to reduce the risk of unforeseen hazards. Additionally, according to the system identification research literature, system identification is a valuable method for better evaluating system dynamics. Safer and more reliable autonomous vehicles can be designed in the future once a better understanding of system dynamics is forthcoming and based on the use of more accurate system identification methods. With safer and more reliable autonomous vehicles in use, scientists will most certainly be able to broaden the tools necessary for the future collection of valuable, scientific data. Future planning to developed a system identification model for a multi-wheeled combat vehicle by get the relation between the input /output signals from the system. A consequently it will be permit to developed a different control method to improve the vehicle performance.

Acknowledgements

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References

Aitouche, A. and Ould-Bouamama, B. (2010) 'Sensor location with respect to fault tolerance properties', *International Journal of Automation and Control*, Vol. 4, No. 3, pp.298–316.

Aras, M., Shahrieel, M., Rashid, A., Zamzuri, M. and Azhan, A. (2013) 'Development and modeling of unmanned underwater remotely operated vehicle using system identification for depth control', *Journal of Theoretical and Applied Information Technology*, Vol. 56, No. 1, pp.136–145.

Axenie, C. (2010) 'A new approach in mobile robot fault tolerant control, minimizing costs and extending functionality', *WSEAS Trans. Sys. Ctrl.*, 1 April, Vol. 5, pp.205–216.

Azmi, M.N., Aras, M.M. and Harun, M.H. (2017) 'Modelling and control of underwater remotely operated vehicle (ROV) for depth control using system identification', *Proceedings of Mechanical Engineering Research Day 2017*, pp.57–59.

Bader, K., Lussier, B. and Schon, W. (2017) 'A fault tolerant architecture for data fusion: a real application of Kalman filters for mobile robot localization', *Robotics and Autonomous Systems*, 28 February, Vol. 88, pp.11–23.

Benosman, M. (2009) 'A survey of some recent results on nonlinear fault tolerant control', *Mathematical Problems in Engineering*, 1 November, Vol. 2010, pp.1–25.

Bhat, A., Samii, S. and Rajkumar, R. (2017) 'Practical task allocation for software fault-tolerance and its implementation in embedded automotive systems', in *Real-Time and Embedded Technology and Applications Symposium (RTAS)*, April, IEEE, pp.87–98.

Brown, C., Durrant-Whyte, H., Leonard, J., Rao, B. and Steer, B. (1992) 'Distributed data fusion using Kalman filtering: a robotics application', *Data Fusion in Robotics and Machine Intelligence*, San Diego, CA, pp.267–309.

Caron, F., Duflos, E., Pomorski, D. and Vanheeghe, P. (2006) 'GPS/IMU data fusion using multisensor Kalman filtering: Introduction of contextual aspects', *Information Fusion*, Vol. 7, No. 2, pp.221–230.

Chen, S., Guo, Q., Leung, H. and Bossé, E. (2011) 'A maximum likelihood approach to joint image registration and fusion', *IEEE Transactions on Image Processing*, Vol. 20, No. 5, pp.1363–1372.

Chiang, S. (2017) 'Vision-based obstacle avoidance system with fuzzy logic for humanoid robots', *The Knowledge Engineering Review*, January, Vol. 32, pp.1–11.

Crassidis, J.L. and Junkins, J.L. (2011) *Optimal Estimation of Dynamic Systems*, 2nd ed., CRC Press, Boca Raton.

Crisan, D. and Doucet, A. (2002) 'A survey of convergence results on particle filtering methods for practitioners', *IEEE Transactions on Signal Processing*, Vol. 50, No. 3, pp.736–746.

Danescu, R. and Nedevschi, S. (2014) 'A particle-based solution for modeling and tracking dynamic digital elevation maps', *IEEE Transactions on Intelligent Transportation Systems*, Vol. 15, No. 3, pp.1002–1015.

Dixon, W.E., Walker, I.D. and Dawson, D.M. (2001) 'Fault detection for wheeled mobile robots with parametric uncertainty', in *Proceedings. 2001 IEEE/ASME International Conference on Advanced Intelligent Mechatronics,* Vol. 2, pp.1245–1250.

Ducard, G. (2009) *Fault-Tolerant Flight Control and Guidance Systems: Practical Methods for Small Unmanned Aerial Vehicles*, pp.1–20, Springer, London.

Eng, Y.H., Teo, K.M., Chitre, M. and Ng, K.M. (2016) 'Online system identification of an autonomous underwater vehicle via in-field experiments', *IEEE Journal of Oceanic Engineering*, Vol. 41, No. 1, pp.5–17.

Farrell, J.A. and Polycarpou, M.M. (2006) *Adaptive Approximation Based Control: Unifying Neural, Fuzzy and Traditional Adaptive Approximation Approaches*, 1st ed., Vol. 48, John Wiley & Sons, Hoboken, New Jersey.

Fourlas, G., Karras, G.C. and Kyriakopoulos, K.J. (2015) 'Fault tolerant control for a 4-wheel skid steering mobile robot', in *DX@ Safeprocess*, pp.177–184.

Hashimoto, S., Ogawa, T., Adachi, S., Tan, A. and Miyamori, G. (2000) 'System identification experiments on a large-scale unmanned helicopter for autonomous flight', *Proceedings of the 2000, IEEE International Conference on Control Application, Conference Proceedings (Cat. No. 00CH37162)*, Anchorage, AK, pp.850–855.

Hiremath, S., van der Heijden, G., van Evert, F., Stein, A. and ter Braak, C. (2014) 'Laser range finder model for autonomous navigation of a robot in a maize field using a particle filter', *Computers and Electronics in Agriculture*, 31 January, Vol. 100, pp.41–50.

Hoffer, N.V., Coopmans, C., Jensen, A.M. and Chen, Y. (2014) 'A survey and categorization of small low-cost unmanned aerial vehicle system identification', *Journal of Intelligent and Robotic Systems*, Vol. 74, Nos. 1/2, p.129.

Jian'an, X., Mingjun, Z. and Jian, Z. (2005) 'Kinematic model identification of autonomous mobile robot using dynamical recurrent neural networks', *IEEE International Conference Mechatronics and Automation*, Niagara Falls, Ont., Canada, Vol. 3, pp.1447–1450.

Kalman, R.E. (1960) 'A new approach to linear filtering and prediction problems', *Journal of Basic Engineering*, Vol. 82, No. 1, pp.35–45.

Karras, G.C., Bechlioulis, C.P., Leonetti, M., Palomeras, N., Kormushev, P., Kyriakopoulos, K.J. and Caldwell, D.G. (2013) 'Online identification of autonomous underwater vehicles through global derivative-free optimization', in *2013 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, November, pp.3859–3864.

Kok, M. and Schon, T.B. (2016) Linköpings universitet, Tekniska högskolan, Reglerteknik, and Institutionen för systemteknik – '*Magnetometer Calibration Using Inertial Sensors*', *IEEE Sensors Journal*, Vol. 16, No. 14, pp.5679–5689.

Kurashiki, K., Fukao, T., Ishiyama, K., Kamiya, T. and Murakami, N. (2010) 'Orchard traveling UGV using particle filter based localization and inverse optimal control', *2010 IEEE/SICE International Symposium on System Integration*, Sendai, pp.31–36.

Li, X., Xu, Q., Chan, C., Li, B., Chen, W. and Song, X. (2015) 'A hybrid intelligent multi-sensor positioning methodology for reliable vehicle navigation', *Mathematical Problems in Engineering*, Article ID 176947, 13pp.

Li, Y., Li, X., Havyarimana, V., Wang, D. and Xiao, Z. (2016) 'Low-cost sensors aided vehicular position prediction with partial least squares regression during GPS outage', *International Journal of Embedded Systems*, Vol. 8, Nos. 2/3, pp.125–134.

Luo, R.C. and Kay, M.G. (1992) 'Data fusion and sensor integration: State-of-the-art 1990s', in Abidi, M. and Gonzalez, R. (Eds.): *Data Fusion in Robotics and Machine Intelligence*, pp.7–135, Academic Press, San Diego.

Min, K., Oh, J. and Kim, B. (2011) 'Traffic sign extract and recognition on unmanned vehicle using image processing based on support vector machine', *11th International Conference on Control, Automation and Systems, Gyeonggi-do*, pp.750–753.

Mirzaei, F.M. and Roumeliotis, S.I. (2008) 'A Kalman filter-based algorithm for IMU-camera calibration: observability analysis and performance evaluation', *IEEE Transactions on Robotics*, Vol. 24, No. 5, pp.1143–1156.

Mohamed, A., EI-Gindy, M. and Ren, J. (2016) 'Advanced control techniques for unmanned ground vehicle: literature survey', *International Journal of Vehicle Performace*, Inderscince publisher (in production).

Mon, Y.J. and Chung-Li, T. (2013) 'Vision-based obstacle avoidance controller design for mobile robot by using single camera', *International Journal of Computer Science Issues (IJCSI)*, Vol. 10, No. 2, pp.10:248.

Nourizadeh, P., Ayati, M. and Yousefi-Koma, A., (2015) 'System identification and model validation of nonholonomic wheeled mobile robots', in *2015 3rd RSI International Conference on Robotics and Mechatronics (ICROM)*, October, pp.586–592.

Okello, N. and Ristic, B. (2003) 'Maximum likelihood registration for multiple dissimilar sensors', *IEEE Transactions on Aerospace and Electronic Systems*, Vol. 39, No. 3, pp.1074–1083.

Olfa, H., Boumedyen, B., Ahmed, Z. and Naceur, A.M. (2015) 'On fault tolerant control of mobile robot based on fast adaptive fault estimation', *2015 IEEE 12th International Multi-Conference on Systems, Signals & Devices (SSD15)*, Mahdia, pp.1–6.

Oniga, F. and Nedevschi, S. (2010) 'Processing dense stereo data using elevation maps: road surface, traffic isle, and obstacle detection', *IEEE Transactions on Vehicular Technology*, Vol. 59, No. 3, pp.1172–1182.

Paolillo, A., Faragasso, A., Oriolo, G. and Vendittelli, M. (2016) 'Vision-based maze navigation for humanoid robots', *Autonomous Robots*, Vol. 41, No. 2, pp.293–309.

Parhi, D.R. and Singh, M.K. (2009) 'Navigational strategies of mobile robots: a review', *International Journal of Automation and Control*, Vol. 3, Nos. 2/3, pp.114–134.

Rigatos, G.G. (2010) 'Extended Kalman and particle filtering for sensor fusion in motion control of mobile robots', *Mathematics and Computers in Simulation*, Vol. 81, No. 3, pp.590–607.

Rigatos, G.G. (2013) 'Sensor fusion-based dynamic positioning of ships using extended Kalman and particle filtering', *Robotica*, Vol. 31, No. 3, pp.389–403.

Ryu, J.H., Gankhuyag, G. and Chong, K.T. (2016) 'Navigation system heading and position accuracy improvement through GPS and INS data fusion', *Journal of Sensors*, pp.1–6.

Sahu, B.N. and Dash, P.K. (2011) 'Development and implementation of a novel adaptive filter for non-linear dynamic system identification', *International Journal of Automation and Control*, Vol. 5, No. 2, pp.171–188.

Samal, M.K., Anavatti, S. and Garratt, M. (2008) 'Neural network based system identification for autonomous flight of an eagle helicopter', *IFAC Proceedings*, Vol. 41, No. 2, pp.7421–7426.

Schaub, A., Baumgartner, D. and Burschka, D. (2016) 'Reactive obstacle avoidance for highly maneuverable vehicles based on a two-stage optical flow clustering', *IEEE Transactions on Intelligent Transportation Systems*, Vol. 18, No. 8, pp.2137–2152.

Siagian, C., Chang, C.K. and Itti, L. (2013) 'Mobile robot navigation system in outdoor pedestrian environment using vision-based road recognition', in *2013 IEEE International Conference on Robotics and Automation (ICRA)*, May, pp.564–571.

Thumati, B.T., Dierks, T. and Sarangapani, J. (2012) 'A model-based fault tolerant control design for nonholonomic mobile robots in formation', *The Journal of Defense Modeling and Simulation*, Vol. 9, No. 1, pp.17–31.

Vlantis. P., Bechlioulis, C.P., Karras, G., Fourlas, G. and Kyriakopoulos, K.J. (2016) 'Fault tolerant control for omni-directional mobile platforms with 4 mecanum wheels', *2016 IEEE International Conference on Robotics and Automation (ICRA)*, Stockholm, pp.2395–2400.

Wang, J., Garratt, M., Lambert, A., Wang, J.J., Han, S. and Sinclair, D. (2008) 'Integration of GPS/INS/vision sensors to navigate unmanned aerial vehicles', *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, Vol. 37, pp.963–970

Welch, G. and Bishop, G. (2001) 'Course 8: an Introduction to the Kalman filter', *ACM SIGGRAPH*.

Xian, Z., Hu, X. and Lian, J. (2015) 'Fusing stereo camera and low-cost inertial measurement unit for autonomous navigation in a tightly-coupled approach', *Journal of Navigation*, Vol. 68, No. 3, pp.434–452.

Zhang, Y. and Jiang, J. (2008) 'Bibliographical review on reconfigurable fault-tolerant control systems', *Annual Reviews in Control*, Vol. 32, No. 2, pp.229–252.