University of Essex

Sensors and Data Fusion Algorithms in Mobile Robotics

Technical Report: CSM-422

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10 January 2005

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ISSN 1744 - 8050

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1. **Introduction**

The aim of this report is to provide a broad overview and understanding of sensor technologies and data fusion algorithms that have been developed in robotics in general and mobile robots in particular, with a scope for envisaging their important role in UK robotics research and development over the next 10 years. As we know, sensors provide a robot with a capability of sensing its environment and handling environment uncertainty, and data fusion algorithms are used to effectively reduce sensor inaccuracy and possible false sensory information. Without sensors and data fusion algorithms, the development of autonomous and intelligent robotic systems remains in the realms of science fiction, and no robot is able to present intelligent behaviours and functions well in the real world. Therefore, a huge variety of sensing technologies have been developed to attack many different problems in real-world applications. The key theme of this report is to present a brief review on sensor technology.

After the customary introduction to the problem domain, we begin with a brief description of the current advancement of a range of sensors and data fusion algorithms and the reason why it is so hard in Section 2. Then, a brief summary on sensor and data fusion algorithm development in the UK is presented, including its position in the world in Section 3. Section 4 outlines some open questions on future sensing technologies in robotics. Finally, a brief conclusion is presented in Section 5.

2. Sensor Technology Development

Over the last few decades, many different types of sensors have been developed in the robotics field, some of which have achieved very promising results [6]. This trend has been mainly driven by the necessity of deployment of mobile robots in unstructured environments or coexisting with humans. These sensors are embedded in robot systems, and their functions can be divided into two categorises: one is internal state sensors and another is external navigation sensors. This section presents a brief summary of these two kinds of sensors, as well as why their development is so hard.

2.1 Internal State Sensors

These internal state sensors are mainly used to measure and monitor the internal states of a robot, e.g. velocity, acceleration, attitude, current, voltage, temperature, pressure, balance, attitude, etc, so that static and dynamic system stability can be maintained, and potential robot failure situations can be detected and avoided. There are two kinds of internal state sensors, namely contact and non-contact sensors.

Contact state sensors

All contact state sensors involve direct physical contact with the objects of interest, including micro-switches, touch, force, tactile and potentiometers. These contact sensors are typically employed on robotic manipulators to handle objects, reach a specific location, or protect the robot from colliding with obstacles. These sensors are very cheap, fast response, easy construction and operation. For instance, micro-switches can be attached on the robot grippers or hands to operate as a binary touch sensor in order to detect object presence or absence. Tactile sensors can be built by adopting different technologies such as magnetic, capacitive and piezoelectric. A binary tactile sensor can be used for detecting presence or absence of touch. A 2D tactile sensor can provide information on size, shape and position of an object. This technology is beginning to mature recently and many commercial devices are available for us to use.

However, all contact state sensors provide very limited information and have a short life span because of frequent contact with objects. Also, it is very difficult to develop effective algorithms to interpret data from these sensors in many circumstances, which remains a big challenge for us. A comprehensive survey on robot tactile sensing technology can be found in [21].

Non-contact state sensors

Non-contact state sensors include synchros, resolves, proximity, accelerometers, tilt, compasses, gyroscopes, optic encoders, etc. Since they are not designed for contacting with any object of interest, these sensors have unlimited life span in theory. Both synchros and resolves are rotating electro-mechanical devices and used to measure angular position information with great accuracy although they are normally very large and heavy devices. Gyroscopes have two types: mechanical and optical. Mechanical gyroscopes operate on the basis of conversation of momentum (linear or angular) and in contrast optical gyroscopes have no moving parts and are virtually maintenance free. Both mechanical and optical gyroscopes are widely used to maintain the stability and attitude of robotic systems, especially useful to unmanned fly robots, underwater vehicles, and space robots that navigate in a 3D environment.

In contrast, optic encoders are most popular non-contact sensors used in mobile robots. There are two types of optic encoders: absolute and incremental. The absolute optic encoders are normally used to measure and control the angle of the steering wheel in a wheeled robot for path control. In contrast, incremental optic encoders are used for measuring and controlling motor speed and acceleration in a mobile robot, as well as odometry calculation. It should be noticed that their fundamental weakness in odometry calculation is unlimited accumulative errors.

2.2 External Navigation Sensors

The purpose of external navigation sensors is to measure and abstract the environment features, e.g. range, colour, gap and road width, room size, object shape, etc., so that the robot can correct errors in the world model, detect environment changes, and avoid unexpected obstacles. External navigation sensors could be roughly divided into two types: vision-based and non-vision based sensors.

Non-vision based navigation sensors

There are a variety of types of non-vision based navigation sensors that have been developed based on different physics principles, such as force, magnetic, sound, smell, infrared, optic, acoustical, laser, radio frequency, proximity, satellite and radar. Among these sensors, force and magnetic sensors are passive navigation sensors that do not generate electromagnetic waves. Most of non-vision based sensors are active sensors which emit some kind of energy that travels between transmitters and receivers, and thus clutter the environment.

Both force and magnetic sensors have proven very reliable, and produce little noise. The data measured from these passive sensors is normally easy to understand and easy to interpret. For instance, force sensors can be used to monitor whether there is an object in contact with the robot for the purpose of collision avoidance. Jones and Flynn described how a full-coverage, force-detecting bumper can be implemented on a cylindrical robot for safe operation [16]. An actuated whisker has been recently developed by Scholz and Rahn to measure contacted object profiles for object identification and obstacle avoidance [28].

On the other hand, the measured data from active sensors is the reflection of either the change in emitted-energy properties such as frequency and phase or simple time-of-flight calculation. These sensors normally provide 1D data at a high rate, and demand less computing power than that required by vision-based sensors. They have been widely used for different navigation tasks of mobile robots such as following a safe path, reaching a goal, avoiding obstacles and mapping an environment.

Ultrasonic or sonar sensors are extremely popular in mobile robotics for last two decades since they are cheap and easy operation. Also, they provide direct range information which is very convenient for many real-world applications in which range information is a must. Leonard and Durrant-Whyte developed a RCD model to interpret sonar data for the purpose of mobile robot navigation [18]. Politis and Smith have recently extended Bozma and Kuc's model for classifying different texture patterns of surfaces that are typical pathways for a mobile robot [25]. However, the problem associated with ultrasound sensors are false range readings caused by specularities resulted from their long wavelength. Many algorithms have been developed to reduce uncertainty in sonar range readings such as EERUF (Error Eliminating Rapid Ultrasonic Firing) algorithms developed by Borenstein and Koren [2]. Since EERUF has a fast sampling rate, a mobile robot is able to travel in a densely cluttered environment at a high speed of 1m/s safely.

The satellite based GPS systems and RF positioning systems are widely used in robot localisation, object and human tracking. The use of GPS in outdoor localisation of mobile robots is very common nowadays since the satellites are free available all the time (24 satellites at a height of about 6900 nautical miles in the sky). The absolute 3D position of any GPS receiver is determined through simple triangulation technique based on time-of-flight radio signals that are uniquely coded and transmitted from the satellites. The main problems of GPS systems include: i) time synchronisation between satellites and the receiver; ii) precise real-time location of satellites; iii) difficult to measure signal propagation time; and iv) electromagnetic noise and other interference. The possible solution is the integration of GPS and other navigation sensors, such as inertial sensors in the system to fuse data and reject noise. Panzieri et al. developed an outdoor navigation system using GPS and inertial sensors [22], in which a Kalman filter was adopted to fuse GPS data and inertial data so that uncertainty in GPS data can be effectively reduced.

The use of odor by insects has motivated robotics researchers to develop the odor detection system for assisting mobile robot navigation tasks. In their earlier work, Deveza, et al. developed an odor sensing system which allows a mobile robot to follow trails of volatile chemicals layered on the floor [4]. An improved odor sensing system was developed, in which the sensor uses controlled flows of air to draw odor laden air over the sensor crystal to increase its response speed [26]. Therefore, odor markings on the floor can be reliably detected and accurately localised. Sanchez-Montanes and Pearce did some theoretic investigation on optimising the performance of odor sensors based on fisher information theory [24]. However, it remains to be seen that this kind of odor sensing systems may be effectively applied to useful robotic tasks, especially in a hazard environment and a disaster rescue site.

Vision based navigation sensors

Robots must be able to see if they are to perform specific tasks such as assembly, inspection and recognition. Vision based navigation sensors mimic our human eyes and can provide huge amount of information, which is one of the most powerful sensors in mobile robotics. However, the visual information obtained from a vision sensor needs three processing stages: image transformation, image segmentation and analysis, and image understanding, which are extremely time consuming and very difficult to achieve in real time in many circumstances, especially when colour image data is considered.

In general, vision sensors used in mobile robots are in the form of CCD (charge-coupled-device) and can be divided into two categories: active or passive. Active vision uses some kind of structured lighting to illuminate the scene and enhance the area of interest in order to make image processing much fast, i.e. only the data in the enhanced area is processed. For example, by projecting a pattern of light strips into the scene, the depth information can be obtained by looking for discontinuities or deformation in the resulting line image. The JPL researchers used a light striping system in the Sojourner Mars rover for obstacle avoidance, in which five lines of light strips were projected ahead of the rover to detect any unexpected obstacle [29].

In contrast, passive vision works under normal ambient illumination condition and have to deal with difficult problems associated with shadows, intensity, colour, texture, and specularities. The large quantity of image data has to be processed in real time in order to abstract useful information for the navigation purpose. Passive vision sensors have been widely used in both indoor and outdoor navigation for different kinds of mobile robots such as wheeled, legged, tracked, underwater and flying. They are mainly used for object and landmark recognition, line following, and goal seeking tasks. For instance, Saripalli, et al. adopted a vision sensor to implement visually guided landing of an unmanned helicopter [27]. In their system, the helicopter updates its landing target parameters based on vision data and uses on-board behaviour-based controllers to follow the path toward the landing site and land on the target with 40cm position error and 7 degrees orientation error. Minten, et al.

developed a docking behaviour for a pair of mobile robots (mother and daughter) based on low-level-complexity vision sensor and an un-obstructive artificial landmark. The vision sensor directly detects and recognises the landmark on the mother robot so that a micro-rover is able to return to its mother body from an approach zone with a 2m radius [20].

2.3 Sensor Interpretation Algorithms– why it is so hard

Different sensors described above provide different kinds of information, including range, size, shape, colour, angle, force, etc. Therefore, each sensor only obtains a partial view of the real world, and react a certain stimulus from it. It has been a big challenging task for robotics researchers to develop different algorithms to interpret these sensory data before they can be used in control and navigation tasks of mobile robots. There are a number of challenging issues in this process, which can be summarised as follows.

Better quality of sensors

As we know, no sensor works well in all situations and every sensor suffers some kind of drawbacks. The performance of sensors may degrade after a limited life span or under some circumstances. Many sensors have been developed for indoor navigation and have rather limited range and resolutions. For instance, although sonar sensors are widely used in mobile robot navigation, robotics researchers have to spend tremendous efforts on interpreting sonar data so that useful information can be abstracted and separated from noise. In contrast, the range data produced by a SICK laser scanner has much higher angular and range resolution, which can be easily interpreted and used for navigation tasks. Jensfelt and Christensen used a SICK laser for their robot to implement pose tracking tasks based on a Kalman-filter based approach [15].

Therefore, it is a crucial task to develop better quality of sensors for mobile robot navigation tasks. As mobile robots begin to move into outdoors, underwater and out-space, they demand for more advanced sensors that have a long range and can work well at extreme conditions.

Better sensor models

To interpret sensory data, the construction of sensor models should be carried out based on adequate data sets sampled by these sensors in the real world. Basically, sensor models present a useful description of sensor's abilities and limitation, such as accuracy and variance.

There are two kinds of sensor models used in mobile robotics: one is qualitative and another is quantitative. The qualitative sensor concept was firstly proposed by Henderson, et al. [13], which however has a very limited use in mobile robots up to now. Most of the developed sensor models are quantitative, which provide the foundation for implementation of data fusion. Guassian probabilistic models have widely adopted in a description of the error distribution in measurements for the convenience of algorithm development, typically Kalman filter based algorithms [5].

The sensor models may have to be adaptive if the sensors are to operate in diversified environments that may change over time. Some kind of learning is required to achieve such adaptivity autonomously. It remains a challenging task for robotics researchers to build good and adaptive sensor models which could be updated in real time and handle non-linearity.

Betterd data fusion methods

Different sensors provide different kinds of information, which should be fused together in order to obtain a complete picture of the real world. More specifically, multi-sensor data fusion aims to overcome the limitations of individual sensors and produce accurate, robust and reliable estimate of the world state based on multi-sensory information. There exist various approaches to multi-sensor data fusion, of which Kalman filtering is one of the most significant ones. Methods for Kalman-filter-based data fusion, including state-vector fusion and measurement fusion, have been widely studied over the last 15 years. State-vector fusion methods use a group of Kalman filters to obtain individual sensor based state estimates which are then fused to obtain an improved joint state estimate. Whereas measurement fusion methods directly fuse the sensor measurements to obtain a weighted or augmented measurement and then use a single Kalman filter to obtain the final state estimate based upon the fused observation. Measurement fusion methods generally provide better overall estimation performance, whilst state-vector fusion methods have a lower computation and communication cost and have the advantages of parallel implementation and fault-tolerance.

It is also noteworthy that state-vector fusion methods are only effective when the individual Kalman filters are consistent. In many realistic applications such as navigation and target tracking, the underlying processes are often non-linear, and the consequent Kalman filters are based on linearised process models (Jacobian linearisation or neuro-fuzzy local linearisation) and will usually be inconsistent due to the model errors introduced by the linearisation process. Hence, when Kalman-filter-based multi-sensor data fusion is applied in these practical situations, measurement fusion is usually preferable to state-vector fusion.

3. Summary of UK Robotics Research on Sensors and Data Fusion (in global arena)

UK Robotics research has been in a rather small scale during last 20 years, comparing with Japan, USA, Germany and Australia. In particular, robotics research on sensors and data fusion is distributed within only a few universities and research organisations, including Essex University, Heriot-Watt University, Leicester University, Oxford University, Salford University, Southampton University, University of the West of England, and the University of Wales (Aberystwyth), BAE Systems, Guidance Control Systems and QinetiQ. In this section, we only include few research cases here.

Biosonar sensors

Typically, time-of-flight sonar data has been widely used for object detection and ranging in mobile robotics for mapping and collision avoidance. Apart from this traditional sensing strategy, researchers at Oxford proposed a new sonar sensing strategy based on continuous transmission frequency-modulated (CTFM) sonar signatures [25]. Through frequency modulation of the sonar signal transmitted, both resolution and signal-to-noise ratio are improved in such a sonar sensor. It only requires a single or two measurements to classify the texture of a number of surfaces that may lie on robot pathways. A K-nearest classifier is used to measure the success of classification.

This new sonar system was inspired by the sensing technology used for blind people to navigate. In other words, all targets on the line of sight can be detected instead of only the detection of the nearest object in traditional sonar sensors. Therefore, it can be used to detect textured surfaces in a robot environment, including furniture, wall and floor. This will have the potential to open up new applications in mobile robot navigation.

Laser scanning sensors

The localisation system based on laser scanners and artificial landmarks is a promising absolute positioning technique in terms of performance and cost. Using this technology, the coordinates of artificial landmarks are pre-stored into an environment map. During its operation, the robot uses its on-board laser sensor to scan these artificial landmarks in its surrounding and measure the bearing relative to each of them [2]. Then the position estimation of the mobile robot is normally calculated by using two distinctive methods: triangulation [19] and Kalman filtering algorithm [14].

In general, there are two problems in the system, which affect the accuracy of the position estimation. The first problem is that the navigation system can not work well when some artificial landmarks accidentally change their positions. If natural landmarks are used in the navigation process, updating map is necessary in order to register them into the map during operation. The second problem is that laser measurements are noisy when the robot moves on uneven floor surface. Therefore the accuracy of robot positioning degrades gradually, and sometime becomes unacceptable during a continuous operation. Therefore, re-calibration is needed from time to time and it becomes a burden for the real world application. To effectively solve these problems, researchers at Essex proposed a navigation algorithm [14] that is able to

- Initialise its position autonomously based on Kohonen neural networks from time to time, and
- Localise the robot position by integrating data from optical encoders, laser scanner and sonar by using EKF (extended Kalman Filter).

Currently, researchers at Essex also develop cooperative localisation and mapping algorithms by using a team of mobile robots, in which some mobile robots may play a role as moveable beacons to assist other robots to improve their relative positioning accuracy from time to time.

Chemical sensors

As described above, robotics researchers have investigated a number of chemical sensors in robot navigation tasks, namely electronic noses. This type of sensors has a very wide range of real-world applications from food quality control, medical diagnosis to crime detection. They provide mobile robots with the capability to search for illegal drugs and explosive materials in security applications. They also enable a team of mobile robots to guide themselves in unstructured environments or disaster sites to implement rescue tasks.

Apart from individual chemical sensors, the researchers at Leicester University developed an array of broadly tuned chemical sensors to discriminate complex multi-component odor stimuli in some special applications in which the sensitivity to a number of different chemical compounds is required. Here, the pattern of responses across the array plays a key role in discrimination instead of individual sensor responses. In order to optimise its overall performance, they adopted both geometric based linear algebra and Fisher information approaches to tune individual sensors in the nose [23].

Theory on the selection of Kalman-filter-based multi-sensor data fusion methods

There are two commonly used methods for measurement fusion. The first simply merges the multi-sensor data, increasing the dimension of the observation vector of the Kalman filter, and the second combines the multi-sensor data based on minimum-mean-square-error estimate, keeping the observation vector dimension unchanged. Clearly, by making use of all the raw measurement information the first method should outperform the second method, but the second method has a much lower computational load. Based on a theoretical analysis of the fused state estimate covariance matrices of the two measurement fusion methods, It has been shown that the two measurement fusion methods are functionally equivalent if the sensors, with different noise characteristics, have identical measurement matrices, as often happens in practical applications [8].

This is a very useful theoretical result which provides effective guidance for selecting Kalman-filter-based multi-sensor data fusion methods, as it shows that under certain conditions a much simpler fusion method is able to achieve the same performance achieved by a complicated fusion method. Currently, researchers at Essex and Oxford are working on the SLAM (Simultaneous Localisation and Mapping) problem in order to develop robust navigation algorithms by using a team of mobile robots and single multi-sensor based mobile robot respectively.

Coping with non-linearity

As we know, Bayesian methods provide a rigorous general framework for dynamic state estimation problems such as positioning based on sensory information in robotics, in which the probability density function (PDF) or posterior of the state is constructed based on all the available information including the state space model and sensor measurements. If the state space model and sensor model are linear and Gaussian, the PDF of the state will be a Gaussian and can be determined by the mean and covariance of the distribution. In this case, the Kalman filter provides an optimal and analytical solution to the mean and variance updating.

However, in most real-world estimation problems, such as mobile robot positioning, the state space model is usually non-linear and/or non-Gaussian, and there is no general analytical expression of the required PDF for the non-linear or non-Gaussian problems. The most popular approach to non-linear state estimation is the extended Kalman filter (EKF) based on Jacobian linearisation. A series of neuro-fuzzy approaches have been proposed at Southampton University to local linear modelling and neuro-fuzzy Kalman filters for non-linear state estimation and multi-sensor data fusion [12]. Recently, research on particle filters for coping with the non-linear and non-Gaussian situations in mobile robot positioning and navigation is being carried out at Essex.

4. Open Problems - the big questions

It is clear that different sensors provide different kinds of information and no sensor works perfectly in all real-world applications. How to effectively utilise the positive side of each sensor and avoid its negative side becomes critical for the deployment of mobile robots in the real world. To reach this goal, sensor technology and data fusion algorithms have been a hot research topic and played a key role in the acquisition of more accurate and reliable information for the last two decades. However, there are a number of open problems in both sensor technology and multi-sensor data fusion algorithms that remain to be answered with the next 10 years. We only list some of them here, which we think is important to be aware.

Coping with non-linear and non-Gaussian situations

The most popular approach to non-linear state estimation is the extended Kalman filter (EKF), in which the estimation problem is linearised about the predicted state and the required PDF is approximately expressed as a Gaussian. Other EKF-like methods for non-linear estimation include the Gaussian sum filter [1] and neuro-fuzzy Kalman filter [12]. All the above methods assume that the PDF of the state can be approximated as a Gaussian or mixture of Gaussians. Although it has been demonstrated that the neuro-fuzzy Kalman filter has the better performance than the standard EKF for non-linear state estimation, almost all the EKF-like methods failed in some state estimation problems with strong non-linearity, such as the bearing-only target tracking problem.

Gordon et al proposed a new way of representing the PDF of the state, and developed a bootstrap filter to recursively update the PDF representation, which was shown to be far superior to the standard EKF in the bearing-only target tracking problem [10]. The power of this filter stems from the key idea of representing the required PDF as a set of random samples (particles) with importance weights, rather than as a function over the state space, which is updated recursively by updating these samples and weights. The above idea and method, now commonly known as particle filters, have drawn much attention recently in the general area of non-linear state estimation [7][9][17]. However, how to effectively represent a non-Gaussian PDF and how to implement particle filters in real time autonomous robot navigation still remain challenging.

Characterisation of the uncertainty

Characterising the uncertainties in sensor measurements is still a challenging problem, firstly because there is no general analytical solution to non-linear and/or non-Gaussian situations and secondly because both the environment and sensor working conditions are time-varying in many practical applications. As mentioned in particle filters, Monte-Carlo methods provide a novel approach to non-Gaussian distribution approximation. Multiple models plus adaptive model switching methods provide a divide-and conquer approach to handle complicated uncertain situations. Fuzzy reasoning as a general tool for coping with uncertainty could be useful in characterising sensor uncertainties.

Fuzzy local linearisation (FLL) has recently emerged as a useful divide-and-conquer approach to non-linear process modelling; it distinguishes itself from traditional piecewise linearisation by fuzzy (soft) input space partitioning. Although new methods have been developed for crisp input space partition in piecewise linear modelling, their applications are restricted due to the inherent ambiguity or fuzziness in the input space partitioning based upon its local linearity. FLL provides a potential way to resolve this problem. In an FLL model, local linear models are constructed on local regions generated from the input space partition by fuzzy sets and are combined by membership function weighting. In general, both the membership functions that define the fuzzy sets and the corresponding local linear models need to be identified by using optimisation techniques such as least squares (LS) and least mean squares (LMS), based on observational data and/or fuzzy rules. Expectation-maximisation (EM) is a general technique for maximum likelihood or maximum a posterior estimation and has become an alternative to LS and LMS techniques in solving many estimation problems as the EM technique can provide covariance information about model mismatch.

LS, LMS and EM are frequently used for local model identification. For input space partitioning or membership function construction, evolutionary or growing-pruning algorithms based on optimal criteria, such as structural risk minimisation (SRM), have been developed. For instance, the adaptive spline modelling (ASMOD) algorithm based on the analysis of variance (ANOVA) decomposition has been widely used in spline models for combating the problem of curse-of-dimensionality in high-dimensional system modelling. In many applications where a priori knowledge is insufficient, it is highly desirable to automatically partition the input space using fuzzy sets in an effective (parsimonious) manner. Aiming at resolving this problem, researchers at Southampton decomposed an FLL model into sub-models in an ANOVA form and developed a modified ASMOD (MASMOD) algorithm for automatic fuzzy partitioning of the input space, including automatic determination of the number of local regions [12]. This model construction algorithm essentially decomposes the underlying non-linear process into an additive set of low dimensional sub-models which are individually parameterised, avoiding the curse-of-dimensionality. However, it remains to be seen how it can be effectively used for mobile robot navigation tasks.

Adaptive multi-sensor data fusion algorithms

In most real-world robotics applications, the environment is uncertain and dynamically changing. Adaptive multi-sensor data fusion is essential to the success in these applications. Adaptive techniques are required to decide which sensors should be involved in the sensor fusion and which fusion method should be adopted. A key issue is when and how the adaptation should take place. For this purpose, effective performance feedback signals are required. Due to the efficiency of the EKF-like methods, they are still the main approach to the complex positioning and navigation problem of mobile robots or autonomous vehicles, such as the SLAM problem [5].

However, there exist realistic problems, such as mobile robot navigation with initial robot position unknown or global position estimation, in which the EKF-like methods offer very poor performance. Compared to the EKF-like methods, particle filters do not need the initial robot position and the linearisation of the state space model. There is only some preliminary work on particle filters for mobile robot localisation [7] or autonomous vehicle navigation [17], reported in the recent couple of years. To the best of our knowledge, there is no reported work from the UK on particle filters for mobile robot localization. Some open problems to be resolved in this area include how to choose and adapt the number of required samples, how to avoid the collapse in the number of distinct values in the sample set, and how to reduce the computational cost.

Decentralised sensor network management

In order to overcome the vulnerability of centralised data fusion systems, decentralised data fusion architectures have been investigated [12]. In a decentralised architecture, there is no global fusion centre, and each local fusion centre provides information with equal importance. Decentralised architectures are flexible, fault-tolerant, and suitable for parallel implementation. However, complicated communication and control mechanisms are needed to coordinate the sensor network (both wired and wireless). Hierarchical data fusion architectures could be a good compromise between centralised and decentralised data fusion, which remains an open research question to be answered within a number of years.

Optimal trade-off between the cost and the gain from multi-sensor data fusion

In general, multi-sensor data fusion is able to produce better joint state estimate than individual sensor based estimate, at the price of using more sensors and more complicated estimation algorithms. An open problem is how much quantitatively the gain from data fusion is and whether the gain is worthwhile considering the cost of multiple sensors and the data fusion system. The difficulty here lies in the analytical evaluation of the performance gain by the multi-sensor data fusion. There is a little work in this aspect, although the work in [8] is one of the rare examples.

5. Conclusion

This report presents a brief overview of sensor technologies and data fusion algorithms that have been developed in mobile robotics during last 2 or 3 decades. Although it is not exclusive and is constrained by the allowed page limit, we could see clearly that sensors and their interpretation algorithms play an important role in the development of autonomous and intelligent robotic systems. A huge variety of sensing technologies have been developed, both in the UK and abroad, to attack many different problems in real-world applications.

Since no sensor is perfect and no sensor suits all the applications, we are expecting that robotics researchers will continuously develop different kinds of better sensors and better data fusion algorithms within next few decades. In other words, we predict not just a quantitative expansion of different kinds of sensor technologies, but also qualitative advancements. Sensors have to scale down to be embedded into micro robots and to scale up to support ubiquity. It is no doubt that sensors will go wild, i.e. everywhere and every networks (wired or wireless), apart from individual robots.

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