Intelligent Leader-Follower Behaviour for Unmanned Ground-based Vehicles

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Abstract:

In this paper an autonomous leader-follower is presented and tested in an unknown and unpredictable environment. Three different types of controller named as First principles-based proportional (P) controller, Fuzzy Logic Controller, and Model-based Predictive Controller are developed and tested in real-time to provide a smooth following behaviour. The follower used the leader's status sent by a smart phone to differentiate between obstacles and the leader and then using two types of sensor, laser and sonar, during the obstacle avoidance procedure. In order to identify the leader again out of many obstacles around, two alternative techniques are proposed using superposition of the scans collected by the laser and predicting the leader's trajectory using evolving Takagi-Sugeno (eTS). At the end, experiments are presented with a real-time mobile robot at Lancaster University.

Keywords: *leader-following robot, human-robot interaction, evolving Takagi-Sugeno.*

1. Introduction

The role of robotics has grown significantly in wide variety of applications such as defence, security, industry, etc.

Many autonomous robots are developed to operate with humans in work environments like nursing homes [1], hospitals [2] and office buildings. In order such robots to be socially acceptable to people, they need to interact with humans and navigate in such a way that people expect them to do without using specific technical expertise. Also, in some applications robot is required to operate in an unknown environment and needs to posses the capability of performing multitude of tasks autonomously without complete a priori information while adapting to continuous changes in the working environments [3]. This paper focuses on the ability of mobile robots to follow a moving object/leader. Following the leader can present significant challenges. In order to follow moving objects in an unknown environment, the robot should be aware of the surrounding obstacles and also be capable of distinguishing obstacles from the leader. Furthermore, the follower should be aware of any, possibly unpredictable, behaviour of the leader beforehand and respond to that.

This paper describes an intelligent person-follower behaviour for Unmanned Ground-based Vehicles (UGV) aiming to follow the movements of the leader with unknown trajectory or kinematic model of motion. The proposed behaviour requires minimal or no intervention from the leader while following him/her in an unknown and unpredictable environment. It should be highlighted that it operates autonomously with high-level of intelligence and situation awareness in contrast to currently available UGVs which are operated remotely, but manually [4], [5] and often rely on GPS or pre-loaded maps.

The remainder of the paper is organized as follows. First, in Section 2 related works on person-following under investigation is summarized and some challenges in leader-follower tasks are pointed out. The proposed approach is briefly outlined in Section 3. Section 4 describes the basic follower by introducing three different controllers, namely, a first principle controller, a fuzzy logic controller, and a predictive controller. Section 5 introduces detecting obstacles and the method for differentiating them from the leader. Sections 6 and 7 describe status of the leader's motion and obstacle avoidance behaviours. Section 8 describes how the follower rejoins the leader after avoiding the obstacle. Section 9 displays the experimental results. At the end, Section 10 provides conclusion and future works.

2. Related Work

One of the most common methods in person following is to use an external device to attach to a person/leader or wearing an emitting device located in the range of sight of the mobile robot [6], [7]. However, existing systems that provide positioning information are not a practical solution since they mostly rely on pre-installed and calibrated environment infrastructures [7]. Several researchers have investigated using a camera for tracking moving objects. In [8] a camera-based method is used for face detection of the leader; nevertheless, this method is not robust due to varying background colour and illumination conditions as the robot moves through various environments. Tarokh and Ferrari [9] implemented a fuzzy controller with camera-based target-position estimation to produce steering speed commands to keep the moving target centred in the camera view. In order to improve the target recognition algorithm, they allowed a few objects besides the target to enter the camera's field of view [9]. To address the difficulties of the camera-based method for person-following, the method developed in [10], [12] integrated laser-based and camera-based techniques together. Laser is used to find the leader's legs and a camera to detect the leader's face. Using face detection, however, requires the leader always to face the robot, and is, thus, practically impossible and inconvenient for the leader when the robot follows the person behind. On the other hand, Cielniak and his colleagues used an omni-directional camera [11], which requires a new training of an artificial neural network for each person that needs to be followed. Such a requirement restricts the generality of the method. Other methods for person-following require a previously acquired map of the environment. Montemerlo and colleagues developed a laser-based leader-follower using mobile robots [13]. However, in order to follow a person by a robot a prior map of the environment is required which makes the method unsuitable for cases where a map of the environment is unavailable or the robot is required to frequently change the place during its operation. Our proposed approach is similar to Shaker and Saade [14], who use a laser range finder to detect a person's position providing distance information to the system for the control process. However, they used the relative velocity of the robot to the person's leg and the difference between the relative distance and the safe distance in [14] instead of using the angle/bearing of the robot towards the moving object (leader) as the inputs of the fuzzy inference system as we do. Moreover, the authors of [14] did not address the challenge when the robot meets an obstacle and the algorithm is only tested in indoor environment when no other obstacles are around.

3. The proposed approach

The approach introduced in this paper is innovative and has been implemented on a laboratory demonstrator for UK Ministry of Deference (MoD) funded project [31]. It has a hierarchical architecture and three main layers (Fig. 1). The Basic Follower procedure is operating in the first layer which will be explained in more details in the following section. The second layer is activated only when the follower meets an obstacle and avoids it by manoeuvring around. At the third layer, the follower determines the current position of a person and rejoins the leader.

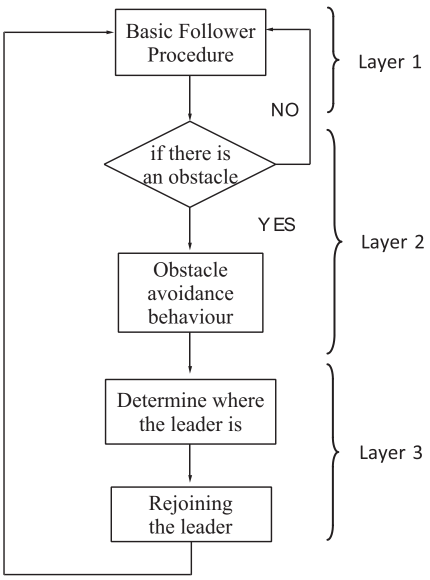

Fig. 1. Schematic representation of the proposed approach with its three layers: 1) Basic Follower; 2) Obstacle avoidance; 3) Rejoining.

The key feature of the person-following behaviour is maintaining a distance and heading of the robot directed towards the leader [15]. The robot has to maintain a certain safe distance from the leader and, at the same time, follow the leader in a smooth motion. To achieve a robust tracking, a first principle controller based on the linearization error [16] is used. Alternatively, in order to obtain more accurate tracking, a fuzzy controller can be applied. Note, that a well-tuned fuzzy controller [17], [23] can also achieve a higher accuracy comparing to the simple linear controller. However, the challenging issue to the conventional controllers is that they generate the manipulated value (control command) according to the observation of system status at the current and the past time instants while the purpose of the control is to minimise the observed error in the forthcoming (future) time instant. Taking into account the dynamic nature of the target system, this delay, in turn, may lead to larger errors. In order to minimise the response delay and improve the control quality, we propose a predictive controller using evolving Takagi-Sugeno (eTS) fuzzy rules [19], [20] as a model predictor. This novel method [18], [19] allows the TS fuzzy model to be designed on-line during the process of the control and operation. This is especially suitable for applications such as UGV autonomous navigation where the mobile robots operate in an unknown environment [21].

The person-follower algorithm has the role of providing the information needed by first principle/fuzzy/ predictive controller to control the motion of the robot. The algorithm analyses the information provided by the laser sensor to detect the position of the leader. Laser provides the distance, d relative to the robot and angle/bearing towards the moving target, θ measured in real-time (Fig. 2). The obtained relative distance and relative bearing are then made available as input information to the controller. The outputs (control action) are the velocities of the robot's wheels which will determine how much speed change is needed by the robot in order to follow the leader.

The aim is maintaining a pre-defined distance, d_{ref} and a bearing angle of 0° so that the target is closely followed without a collision to any obstacle. Note, that due to unpredictable movement of the target/follower, there will be some misalignment between the heading of the leader and the robot (bearing θ in Fig. 2).

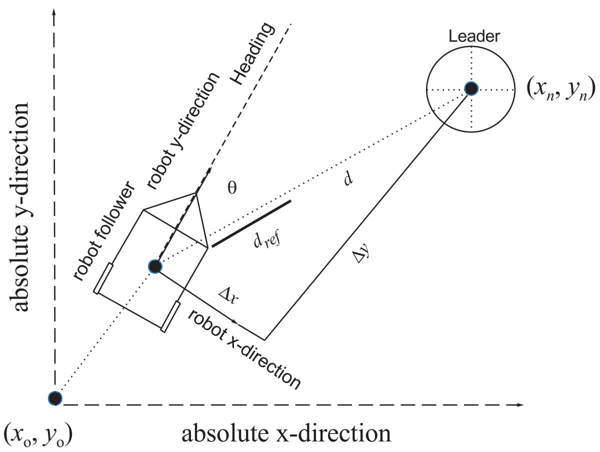

Fig. 2. The leader (target) and the follower attempting to keep a constant distance, dref and to nullify the misalignment, θ.

In an unknown environment, the follower should be aware of all surrounding obstacles and have enough intelligence to detect and avoid them. To make this happen, we propose two conditions to be checked by the follower. The first condition is a sudden and large drop in the distance which causes the negative velocity of the wheels; the second alternative condition is the signal from the leader which indicates its motion status.

After collision detection and avoidance procedure, the follower should be able to determine the new position of the leader out of, possibly, many objects in front of it, and rejoin the leader again. Two alternative techniques aiming to identify the current position of the leader are introduced which rely on the prediction of the trajectory of the leader and on super-positioning of the scans taken by the laser.

The proposed approach for person-following will be explained in more details in the following sections.

4. Basic Follower

In order to track the leader, the heading of the mobile robot is controlled indirectly through the difference of the velocities of both wheels. Three alternative controllers are used to control the robot motion while following a person.

1) First principles-based proportional (P) controller;
2) Fuzzy Logic Controller (FLC);
3) Model-based Predictive Controller (MBPC).

4.1. First Principles-based Controller

The *P* controller is based on the explicit linear description of the problem. It keeps acceleration of the robot proportional to the distance to the target/leader, *d* [22]. Due to the inertia of the real systems it takes a short period of time after a velocity command is received by the motor for the desired velocity to be reached. The velocities of both wheels (left and right) are selected as control values and the turning of the robot is achieved by control of the velocity difference between the left and right wheels. When the velocity of the left wheel is higher than the velocity of right wheel, the robot makes a right turn and vice versa. Based on these principles, the wheel velocity control model is described by the following equations:

$$\begin{aligned} V_{left} &= V_f + V_l \\ V_{right} &= V_f + V_r \end{aligned} \tag{1}$$

It consists of two components; V_f the component for maintaining d_{ref}, and the pair of velocities V_i and V_r to determine the heading of the mobile robot. The two components are defined by the following equations:

$$V_f = k_1(d - d_{ref}) \tag{2}$$

$$V_l = \begin{cases} 0 & |\theta| < \bar{\theta} \\ k_2\theta & |\theta| > \bar{\theta} \end{cases} ; \quad V_r = \begin{cases} 0 & |\theta| < \bar{\theta} \\ -k_2\theta & |\theta| > \bar{\theta} \end{cases} \tag{3}$$

where $\bar{\theta}$ is threshold of insensitivity which filters the sensors; k_1 and k_2 are proportionality coefficients. $k_1 = 2$ and $k_2 = 3$, are chosen based on preliminary tests)

Fig. 3 depicts the linear proportionality between; a) the velocity of the robot and distance to the target measured from the robot (Fig. 3a); b) the heading angle (determined by the left and right velocities) and the angle/bearing to the target/leader respectively (Fig. 3b). When the distance between the robot and the target is too large, the velocity component V_f gets a higher value in order to maintain the d_{ref} which leads to a large acceleration of the robot. However, if the distance is smaller than d_{ref} (the required reference distance we want the UGV to follow the leader at), the velocity component, V_f is set to Negative. The technical limit of the Pioneer 3-DX robot is $V_{max} = 1400$ mm/s.

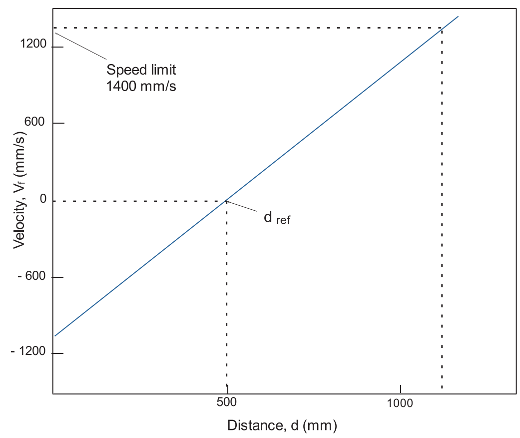

Fig. 3a. Distance component.

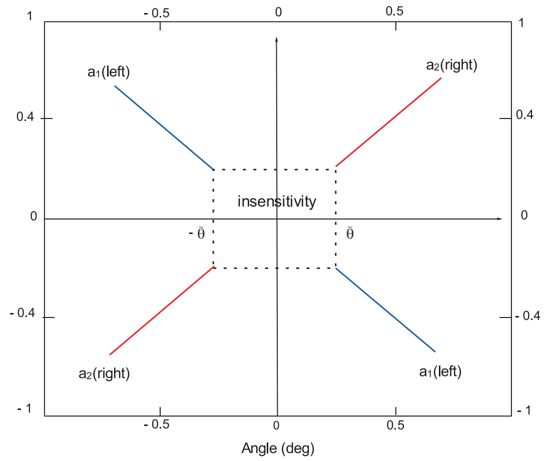

Fig. 3b. Angular component.

$$when_r = \ |\theta| < \bar{\theta} \ ; \ a_1 = a_2 = 0 \tag{4.1}$$

$$when_r = \ |\theta| < \bar{\theta} \ ; \ \begin{cases} a_1 = -k_2 \times \theta \\ a_2 = k_2 \times \theta \end{cases} \tag{4.2}$$

4.2. Fuzzy Logic Controller (FLC)

Fuzzy controllers have recently been used in a variety of applications such as underground trains, robotics, etc. owing mainly to their flexibility and higher accuracy which is achieved due to their non-linearity. The data from the detection of moving objects provided by the laser is, sometimes, noisy and could be, occasionally, incorrect. Therefore, in order to provide a more flexible (non-linear) relation between the inputs (distance and bearing to the target/leader) and outputs (the velocities of both wheels), a Zadeh-Mamdani type FLC [23] has been implemented which consists of twenty five fuzzy rules (Table 1) for each left/right robot wheels.

Table 1.a. Rule table of "Left Velocity".

θ \ d	Crash	Close	Proper dist.	Not Far	Far
N	QB	QB	H	QF	QF
SN	QB	SB	H	SF	QF
S	QB	SB	H	SF	QF
SP	QB	SB	H	H	SF
P	QB	SB	H	H	SF

(N=Negative, SN=Small Negative, S=Small, SP=Small Positive, P=Positive, QB=Quick Backward, SB=Slow Backward, H=Hold, SF=Slow Forward, QF=Quick Forward)

Table 1.b. Rule table of "Right Velocity".

θ \ d	Crash	Close	Proper dist.	Not Far	Far
N	QB	SB	H	H	SF
SN	QB	SB	H	H	SF
S	QB	SB	H	SF	SF
SP	QB	SB	H	SF	QF
P	QB	QB	H	QF	QF

Each rule represents a typical situation during the "Leader following" task. The input vector is formed based on real-time measurements by the sensors (laser or sonar) providing the distance, d and angle/bearing θ (see Fig. 4).

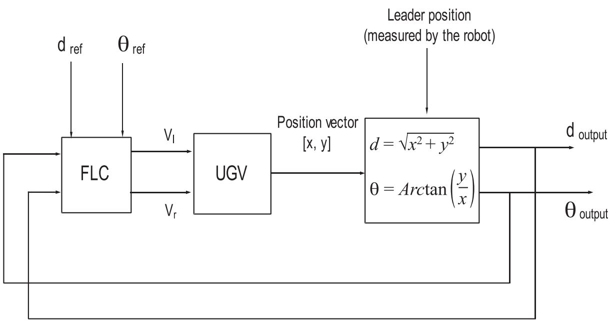

Fig. 4. FLC schematic diagram.

The closeness between the measured input vector and the focal points of each fuzzy set is calculated based on triangular/trapezoidal membership functions illustrated in Fig. 5. The result is aggregated to form the degree of firing for each rule and normalized and aggregated further to form the overall output of the FLC [23].

$$\tau_i = \mu_{i1}(d) \times \mu_{i2}(\theta) \qquad i = [1,..., R] \tag{5}$$

where μ_i denotes the i^{th} membership function; d and θ are the inputs; R - number of the fuzzy rules, R=25.

The commonly used aggregation method called "centre of gravity" is applied to determine the firing strength of each fuzzy rule as follows:

$$\lambda_i = \frac{\tau_i}{\sum_{i=1}^{R} \tau_i} \tag{6}$$

$$\begin{bmatrix} V_l \\ V_r \end{bmatrix} = \begin{bmatrix} \lambda_1 & \lambda_2 & .... & \lambda_R \\ \lambda_1 & \lambda_2 & .... & \lambda_R \end{bmatrix} \begin{bmatrix} a_{11} & a_{21} \\ a_{12} & a_{22} \\ \vdots & \\ a_{1R} & a_{2R} \end{bmatrix} \begin{bmatrix} d \\ \theta \end{bmatrix} \tag{7}$$

where $a=[a_{11},...,a_{1R};a_{21},...,a_{2R}]$ are the parameters of the consequent part of the FLC.

The antecedent part of the fuzzy rules is defined by linguistically interpretable terms that describe the distance (Fig. 5a) and angle/bearing (Fig. 5b); the consequent fuzzy sets are defined in respect to the left velocity and right velocity (Fig. 6).

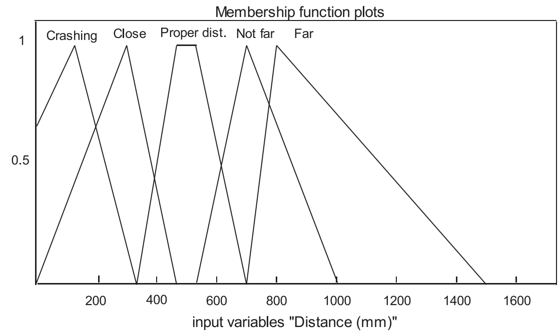

Fig. 5a. Fuzzy sets for distance (mm).

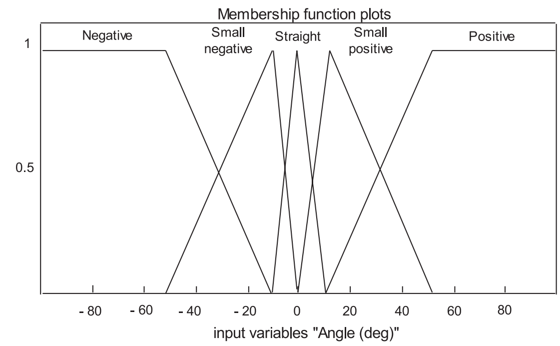

Fig. 5b. Fuzzy sets for angle/bearing (deg).

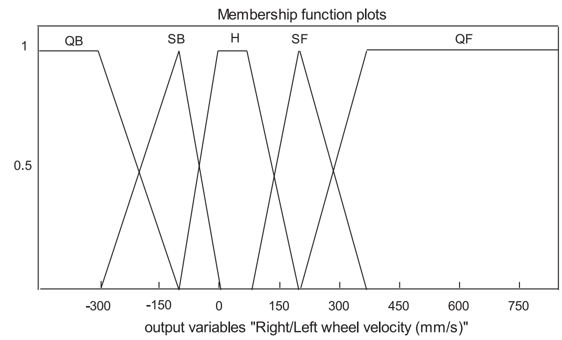

Fig. 6 Fuzzy sets for left/right velocity (mm/s).

4.3. Model-based Predictive Controller

As mentioned earlier, the key aim in using a controller is to minimise the observed error provided by the observation of the systems status at the current and the past time instants. However, delay in response caused by dynamic nature of the target may lead to large errors. In order to minimise the error caused by the delay, a more advanced class of controllers is used, namely model-based predictive controllers (MBPC) [24], [27]. MBPC is an optimal control strategy that uses the dynamic model of the system to obtain an optimal control sequence by minimising an objective function (8).

The MBPC used employs a discrete-time prediction model and control law. The discrete-time model of the robot motion used can be given by [35]:

$$\begin{cases} x(k+1) = x(k) + v(k)\cos\theta(k)T \\ y(k+1) = y(k) + v(k)\sin\theta(k)T \\ \theta(k+1) = \theta(k) + \omega(k)T \end{cases} \tag{8}$$

where v and ω are the linear and angular velocities; and T is a sampling period.

In a general, state space form it can be given as:

$$X(k+1) = f_d\,(X(k), u(k)) \tag{9}$$

where $u = [v\ w]^T$ is the control input; and $X = [x\ y\ \theta]^T$ describes the configuration

The leader's trajectory x_n and the robot motion control (velocities) vector, u_n are related by:

$$X_n(k+1) = f_n\,(X_n(k), u_n(k)) \tag{10}$$

The problem of trajectory leader tracking can be stated as "to find a control law in such a way that at any time instant", k satisfies:

$$X(k) - X_n(k) = 0 \tag{11}$$

This tracking problem is solved by employing MBPC. At each sampling instant, the model is used to predict the behaviour of the system over a prediction horizon, H_p. The predicted output values, denoted $X(k+j)$ *for* $j = 1,..., H_p$ depend on the state of the process at the current time instant, k and on the future *control signals*, $u(k+j)$ *for* $j = 0,..., H_c - 1$, where H_c is the *control horizon*. The sequence of future control signal $u(k+j)$ *for* $j = 0,..., H_c - 1$, is computed by optimising a given objective function, in order to track the reference trajectory, x_r as close as possible [27], [37].

$$J = \beta \sum_{j=1}^{H_p} [X_r(k+j) - X(k+j)]^2 + \lambda \sum_{j=1}^{H_c} [\Delta u(k+j-1)]^2 \tag{12}$$

where $\beta \geq 0, \lambda \geq 0$ is the output error and control increment weighting

The first term accounts for minimising the variance of the process output from the reference, while the second term represents a penalty on the control effort.

Ohya and Monekata [24] proposed an algorithm to predict the next position and speed of the leader based on the history of the leader's position with time instance recorded. However, they assume that the leader will move with the constant acceleration and same angular velocity, which is unrealistic. On the other hand, some other approaches [25], [26] propose using the predictive target tracking algorithm based on the well established Kalman filter and report achieving high reliability. Babuska [27] used a Takagi-Sugeno (TS) fuzzy model as a model predictor; however, the model was predefined off-line with a fixed structure which assumes knowing the order and nature of the non-linearity associated with the leader's motion. In this paper, we propose to go further and use evolving Takagi-Sugeno (eTS) fuzzy ruled-based systems [18-20], [36] which requires no assumptions on the order and complexity of the non-linearity and the structure of the controller. We propose a MBPC that is using eTS (eMBPC) to predict the next position of the leader online for a horizon of several steps ahead based on the historical observations (time-series of realtime readings).

$$x_{k+H_p} = eTS(x_k, ..., x_{k-\Delta}) \tag{13a}$$

$$y_{k+H_p} = eTS(y_k, ..., y_{k-\Delta}) \tag{13b}$$

where $eTS(.)$ is a short-hand notation for the eTS fuzzy rule-based model and Δ-represent the memory used.

In this technique, the controller continuously estimates the future predicted position of the leader as he/she moves. Once the leader's future position is estimated, the motion controller implements the required control signals to the robot wheels having in mind the ***future*** position of the leader. This leads to minimising the tracking error caused by the delay in response of the controller and increasing the performance and reliability of the Leader following behaviour.

MBPC operates in real-time, on-line and is self-learning (both in terms of its parameters and in terms of its structure). Moreover, it does not need to be fed by an initial structure or tuned which makes it generic. The data are processed on-line (in one-pass) and, therefore, it requires very limited computational resource and is suitable for on-board implementation on the mobile robots (UGV). The improved performance of the prediction is discussed in Section 8.

5. Detecting Obstacles

Differentiating between an obstacle and the *leader* is one of the challenging aspects of this task. As mentioned earlier, in Section 3, distance and angle/bearing to the nearest object are used as inputs of the controller. If the leader disappears from the view of the robot after meeting and obstacle (for example quickly avoiding it), the latter may be misled. The robot may find it difficult to distinguish between cases when the leader stopped and cases when the leader quickly disappeared and the nearest object is, in fact, an obstacle that needs to be avoided. The UGV should have enough intelligence to differentiate between these two cases which may look similar if only distance and bearing are used as inputs. To address this problem, we proposed two conditions to be checked;

i. Sudden large drop of the distance
ii. Signal related to the leader's motion status

If the distance to the leader suddenly drops significantly (more than d_{ref}), the robot moves backwards to maintain the reference distance which leads to a negative velocity of the robot wheels (Zone B, Fig. 7). Such moves (that lead to a distance drop) often take place during the process of leader following (Zone A, Fig. 7) but the amount of the distance drop is usually not large since the controller aims to minimise the deviations from d_{ref}. However, when an obstacle is detected or the leader stops the distance drop is large and sudden (contrast zone B to zone A, Fig. 7).

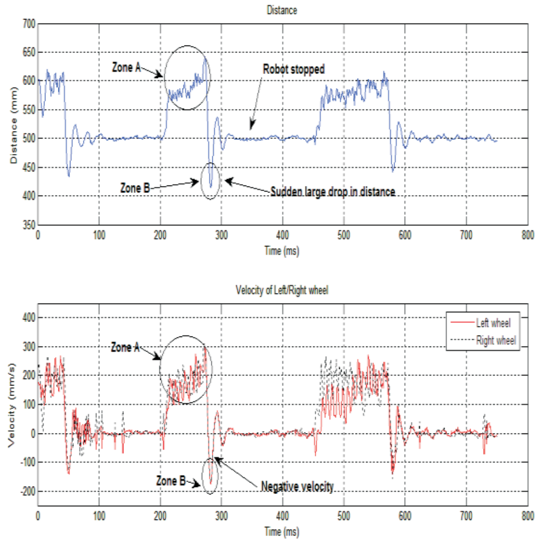

Fig. 7. Distance and velocity of the wheels measurements (data from the real-life experiment).

The second condition assumes a short informative signal from the leader to be sent wirelessly which indicates its motion status (to be described in more detail in Section 6).

Summarising, the two conditions used to distinguish the leader (when (s)he stops) from an obstacle are formulated as; i) the mean velocity of both wheels to be negative, and; ii) the leader to have motion status '*walking*'. If both conditions are satisfied at the same time, the robot starts executing an obstacle avoidance manoeuvre (to be described in Section 7). This part of the algorithm can be illustrated by the following IF-THEN rule.

IF (mean velocity) < 0 && (leader's status is 'walking')

{

Obstacle Avoidance procedure

}

Else

{

Basic Follower procedure

}

After avoiding the obstacle, the robot switches again to the Basic Follower procedure (layer 1, Fig. 1).

6. Status of Leader's Motion

A very robust and effective way of informing the robot about the motion status of the leader (walking or stopped) is by using a very short signal emitted by a device carried by him/her, e.g. The latest generation smart phone (Nokia N97) which includes several on-board sensors and more than enough processing capacity to handle them. Eventually, this off-the-shelf device can be substituted by a much smaller purpose-build microprocessing system. Nokia N97 has on board an ARM11 343 Mhz processor and works with Symbian OS v.9.4. The selected technology to connect the robot and the leader was Wi-Fi upon the 802.11 b/g standard [33]. We also experimented the use of another (3G) mobile connection technology; however, it entails the installation of third party antennas which would make system deployment very complex. Therefore, Nokia N97 was selected.

Note, that the message that is transmitted between the Nokia N97 and the on-board computer of the Pioneer robot is extremely short (few bits - the status can be a single bit 0/1 plus the address of the receiver in a datagram packet) and can be sent at an extremely low bit rate (it can be done only by request from the robot when in Zone B, Fig. 6) - this situations practically occurs quite rarely, e.g. with a frequency in mHz range).

The smart phone Nokia N97 offers some useful features such as; the accelerometer, orientation, azimuth, GPS data, and distance to the nearby objects by a proximity sensor. We discarded GPS data because it implies using satellite connections and also proximity sensor as lacking enough range and precision.

From a software point of view, the smart phone has a Java Midlet (J2ME). At the receiver side (the robot/UGV) a Java Application (J2SE) is deployed on its on-board computer [28]. This application is in charge of gathering all datagram packets sent by the smart phone *via* UDP/IP protocol. TCP/IP connections were initially discarded because no order of the data is required, hence giving priority to the speed of the reply. Using the UDP datagram protocol allows establishing a connectionless network (the address is a part of the packet) which is a convenient solution for the particular problem. The sampling rate (with which the raw data of the acceleration of the leader are being collected) is being set by default to 40 Hz. The data from the internal (to the smart phone) sensor have been filtered and processed before sending over the channel to avoid peaks and outliers in the signal and to minimise the communication (sending the status data instead of the raw acceleration data reduces the bitrate and the possibility of an interception dramatically). The robot requests a signal from the leader's device only when Zone B, Fig. 6 occurs (either when the leader stops or an obstacle obstructs suddenly his/her way). It is important to stress again that the latter situation happens very rarely with a frequency in mHz range.

7. Obstacle avoidance behaviour

The ability to avoid obstacles is one of the most fundamental competences in mobile robotics and autonomous systems. In order to prevent collision with obstacles, the follower (UGV) should have Obstacle Avoidance behaviour. In our case, after the follower successfully distinguishes an obstacle from the leader, the Obstacle Avoidance procedure is being activated. In order to increase its reliability, we used two types of sensors, sonar and laser. Sonar sensors are used to check if the UGV fully passed the obstacle, and laser, alternatively, is used to monitor if there are no obstacles between the robot and the leader. As a result, the UGV successfully avoided all obstacles that were identified (see Section 9 for the experimental result).

8. Rejoining the leader

After an obstacle is being avoided, the UGV have to identify the leader/target out of the, possibly, many objects that are visible. Two alternative techniques are proposed for the re-joining the Leader behaviour;

i. Predicting the leader's trajectory
ii. Superposition of the scans taken by the laser

8.1. Predicting the Leader's Trajectory

The module for predicting the movements of the leader contributes to the increase of the situation awareness and enables the UGV to rejoin him/her once the obstacle is being avoided. As described in Section 4.3, we use evolving Takagi-Sugeno (eTS) fuzzy rule-based systems [18-20] for predicting in real-time the position of the leader/target. This is illustrated in Fig. 8 for one step ahead prediction. However, to predict the position of the leader after avoiding the obstacle is very difficult (leader may go to a completely opposite direction). In order to minimise the error and achieve a more precise re-joining behaviour another alternative technique is proposed using superposition of the laser's scan which is explained in more details in the next section.

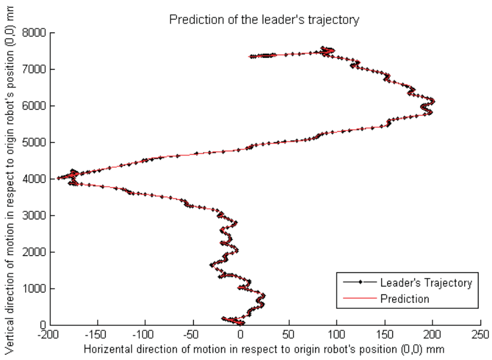

Fig. 8. Leader's Trajectory prediction using eTS (black dotted line - line trajectory of the leader, red solid line - the prediction using eTS).

8.1.1. Superposition of the Laser's Scans

An alternative technique to implement Rejoin the leader behaviour is proposed which is based on super-imposing the scans taken by the laser in real-time. The idea is to subtract the motion of the robot and, thus, to leave the objects that are static clearly separated and visible from the moving objects for which the cloud (cluster) of points will be moving. This is illustrated in Fig. 9.

We propose using online clustering to identify the moving object(s)/target(s) and to distinguish them from the static object(s). The online clustering is based on recursive calculation of the Euclidian distance between the new points in respect to the previously gathered centres [32]. From Fig. 8 it is clearly seen that points which belong to static objects remain in the same place of the space, overlapping the previously gathered points corresponding to the same objects. (The reason that overlap in Fig. 9 is not absolutely perfect is the noise associated with the real measurements and data streams induced from both laser sensor and movement of the robot). However, it is easy to distinguish points which belong to an object from points that belong to moving objects (e.g. the leader). This approach also provides information about the distance in terms of direction of the moving object(s) (e.g. the leader). It is sparse in terms of space with their total mean deviation bigger than the others.

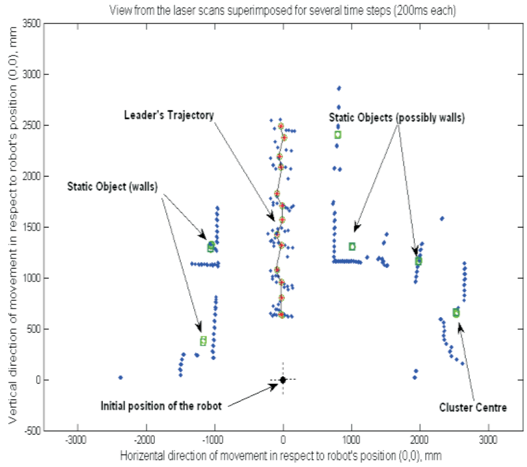

Fig. 9. Scans taken by the laser mounted on the mobile robot. The static obstacles (walls) are clearly seen as clusters of circle dots centers of these clusters were identified on-line as the square dots; one of the cluster centers was moving which indicates the leader - it is shown as a string of cross points (the position of the cluster centers in different time instants are linked with a solid line indicating of the leader's motion direction).

9. Experimental Result

Fig. 10a. Outdoor experiment.

Fig. 10b. Indoor experiment.

The experiment was carried out outdoors (Fig. 10a) and indoors (Fig. 10b) at Lancaster University in October 2009 with a Pioneer 3-DX mobile robot. The Pioneer 3-DX [29] is equipped with a digital compass, a laser, sonar sensors and onboard computer. It is very suitable for various research tasks including mapping, vision, monitoring, localisation, etc [21], [22]. The leader (the role was played by the first author of the paper) carried a late generation smart phone *Nokia N97* in his pocket used only in *wi-fi* mode to provide leader's status ('*moving*' or '*stationary*') as described in Section 6.

The experiment was performed in 3 main phases and was fully unsupervised (without using GPS or any external links; the wireless connection only was used to download data; the only manual intervention was to start and stop the robot). In phase 1, the robot started with the Basic Follower behaviour (layer 1, Fig. 1). In phase 2, in order to test the ability of the robot/UGV to autonomously distinguish obstacles from the cases when the leader stops, he quickly disappeared behind an obstacle (Fig. 11a). The robot detected the obstacle after the two conditions were checked and satisfied (Section 5) and avoided the obstacle successfully (Fig. 11b). In phase 3, both Rejoining the leader behaviours (Section 8) were tested successfully (Fig. 11c).

Fig. 11a. Leader quickly disappears behind the obstacle.

Fig. 11b. Robot avoided the obstacle.

Fig. 11c. Robot searched for the leader and rejoins him.

The video clips from the experiments are available at: http://www.lancs.ac.uk/staff/angelov/Researc h.htm

9.1. Basic Follower

When the Basic Follower behaviour is realised a 90° fan area is being scanned using the laser with 1° resolutions [30]. It returns the distance, *d* and the bearing/angle, θ to the nearest object (Table 2).

Table 2. Example of the data collected in realtime with the control inputs and outputs.

Time (ms)	*d* (mm)	θ (°)	Velocity Left (mm/s)	Velocity Right (mm/s)
0	588.07	–9.13	203.54	148.75
200	563.28	8.30	134.05	183.87
400	570.84	0.467	143.09	140.29
600	583.25	–8.17	191.01	141.99
800	566.37	6.27	131.90	151.57
1000	575.64	18.81	207.7	94.86

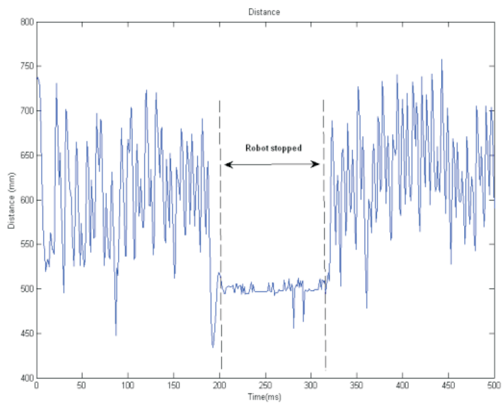

Fig. 12.a. Distance measured in real-time (the interval when the robot stopped is clearly marked; the high variance when the robot is moving is due to the noise and imperfection of the laser scanner and the controller).

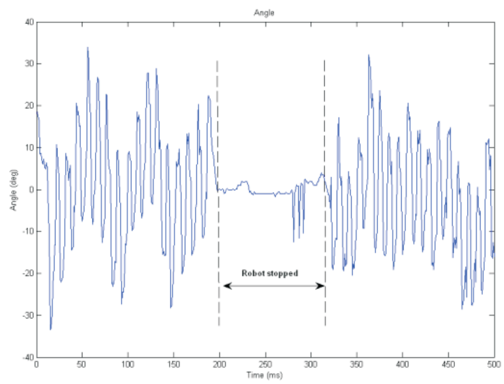

Fig. 12.b. Angle measured in real-time (the interval when the robot stopped is clearly marked; the high variance of the readings when the robot is moving is due to the noise and imperfection of the laser scanner and the controller).

The aim was to control the distance, *d* as close as possible to d_{ref} (in this experiment d_{ref} = 500mm). The sampling frequency was 10Hz (100ms per sample). The control values were generated at each sampling interval. Although, during the experiment the target/leader performed a series of behaviours including acceleration, deceleration, turning, reversing, the UGV, following the leader smoothly and even moving back when the leader stopped (the distance, d became smaller than the distance, d_{ref}).

The velocity was measured by the tachometer (odometer) of the robot [28]. An example of the measured distance and angle to the target is illustrated in Fig. 12.

9.1.1. Controllers Comparison

Traditional (P) controllers are known to be heavily reliant on tuning. Therefore, when a P controller was used it required some tests to establish suitable parameters (k_1 and k_2). FLC was also not free form this disadvantage MBPC is self-learning and, therefore, it did not require extensive prior tuning. Table 2 illustrates the comparison between the three controllers. The discrepancy between the real observation and the target values of distance and angle has been used to calculate the errors. The mean absolute error (MAE) and the root mean square error (RMSE) are used as the criteria for the comparison of the three controllers. As it is clear from the table, predictive controller has assisted the fuzzy controller to achieve a better control performance in terms of distance and to some extent in terms of tracking angle to minimise the delay in control response. FLC also has a better performance compare to P controller in term of distance. In order to improve the angle tracking in FLC which is worse than P controller, more rules describing the response to different observation in angles can be added to the fuzzy controller to achieve higher accuracy. Also, the off-line techniques such as ANFIS [34] can be used in order to get the optimal parameters of fuzzy controller.

Table 3. Result comparison.

	d (mm)		θ (°)	
	RMSE	MAE	RMSE	MAE
P Controller	8.5	150.6	0.53	10.00
FLC	4.93	112.3	0.60	11.21
MBPC	4.45	100.6	0.54	8.58

9.2. Obstacle Avoidance

When the leader meets an obstacle and disappears quickly from the view of the robot, this is detected by activating the procedure described in Section 5 using a signal sent through *wi-fi* connection from the smart phone that the leader carries. Combining the two conditions the robot/follower initiates an obstacle avoidance manoeuvre.

9.3. Rejoining the Leader

This behaviour is activated immediately after the obstacle is being avoided. The challenging part is the need the robot to identify the leader out of many objects. One alternative was to use the prediction (as described in Section 8). Another approach is to super-impose the laser's scans. The following sub-sections describe the results using each of the two techniques.

9.3.1. Predicting the Leader's Trajectory

The precision of the prediction as described in Section 8.1 is in order of 100mm for a prediction horizon of 3-5 s (the prediction horizon is determined by the obstacle avoidance module) [31]. Note, however, that this is an useful range of errors, because the aim is to rejoin the leader after an obstacle avoidance and to approximately identify the location of the leader in such a way that there is no other obstacle in the vicinity of dozen cm which is reasonable, although not perfect. A higher precision may be preferable, but the task is very complex since the motion of the leader, especially, when avoiding an obstacle himself is very difficult to predict for a long horizon. Note, also, that the leader is not a dot in the space, but a physical object with width of about 500 mm.

9.3.2. Superposition of the Laser's Scan

After avoiding the obstacle, the scans are taken by the laser every 200 ms with 180° fan view. The detectable range of the laser is [150; 10,000] mm. However, while the robot is moving, these scans had to be adjusted in respect to an absolute coordinate system (e.g. linked to the initial robot's position), see Fig. 2. This is done by super-positioning scans stored in a buffer and ordered by tuples regarding the time of collection taken at consecutive time instants (Fig. 9). Once several (10-15 in this experiment) scans were collected, the robot could detect the position of the leader (red point) out of several static objects (green point) and rejoin the leader and to continue with the Basic Follower procedure, Fig. 1.

10. Conclusion

10.1. Summary

In this paper we demonstrated a novel approach for leader follower behaviour of UGV in uncertain environment. The hardware specification of the provided platform was a selected Pioneer 3-DX robot with laser, sonar sensors and a compass on board. As an external sensor, a smart phone with accelerometer and a compass on board was also provided.

The software components of the proposed approach were divided in three main layers: following, detecting and avoiding obstacles, and rejoining the leader. Three controllers (the P-controller, FLC, and eMBPC) were applied separately in the Basic Follower layer. In order to detect obstacles and differentiate those from the leader, two conditions were checked; i) sudden large drop in the distance and ii) the current status of the leader provided by the smart phone Nokia N97. When the obstacle is detected, two sensors (laser and sonar) were used for the obstacle avoidance procedure. Finally, in order to rejoin the leader after the robot successfully avoided the obstacle, two alternative techniques were proposed; i) predicting the leader's trajectory, and ii) super-position of the scans taken by the laser. The overall behaviour was tested successfully indoors and outdoors at Lancaster University.

10.2. Future Work

The leader follower behaviour presented in this paper assumed that the robot follows the leader behind. However, in order to develop a robot with social skills and intelligence, it needs to engage the leader and accompany him/her as a human would. We intend to address the issue in our future work by developing behaviours which allow the robot to travel side-by-side with the leader in a socially acceptable manner. Another task is to improve the controller by developing a self-adaptive fuzzy controller which works online without the compulsory need of an offline pre-training and does not need a prior knowledge about the differential equations governing the system. In addition, to improve the robot's performance in identifying the leader out of many moving objects (after avoiding the obstacle), super-position of the scans collected by the laser can be combined with the direction of the movement of the leader measured by the magnetometer of the smart phone carried by him/her. This issue should be addressed in another publication.

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