Biomimetic application of desert ant visual navigation for mobile robot docking with weighted landmarks

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Abstract: Previous work has shown that honeybees use a snapshot model to determine a local vector to find their way home. A simpler, average landmark vector model has since been proposed for biologically-inspired mobile robot homing. Previously, the authors have extended the model to address the problem of docking a unicycle-like vehicle smoothly using bearing-only information and without reconstructing the pose of the vehicle (Wei et al., 2003, 2004). Here, we extend further to consider weighted landmarks, allowing greater control over the shape of the trajectory that the robot will follow. This approach permits docking from a wider range of initial poses, while respecting the kinematic constraints of the robot. The proposed control method has been implemented on the Nomadic Technologies XR4000 robot at ANU using visual landmarks. Experimental results are presented which demonstrate the desired docking behaviour from a broad range of initial conditions.

Keywords: mobile robot docking; biomimetic navigation; panoramic vision; visual landmarks.

1 Introduction

Biology provides excellent examples of simple systems, which can achieve amazing results given the limited resources available. For example, the desert ant *Cataglyphis bicolor* is capable of navigating with pin-point accuracy to find its way home after travelling thousands of times its own body length (Wehner, 2003) (e.g., see Figure 1). It is believed that *Cataglyphis bicolor* employs landmark features for guidance combined with the polarisation pattern of the sky for homing (Lambrinos et al., 1997). It is quite amazing that the ant can perform this feat quite reliably, given that it has an 0.1 mg brain (Figure 1). Experiments with honeybees have studied homing behaviour in detail (Collett et al., 2002; Cartwright and Collett, 1983) and proposed a snapshot model to explain the observed behaviour (Cartwright and Collett, 1983). A simpler average landmark vector model has also been proposed, which delivers similar performance with a more compact representation (Lambrinos et al., 2000). Analogue hardware implementations lend credence to the average landmark vector model as a biological system (Möller, 1999, 2000).
Figure 1 Cataglyphis ants can return home directly after foraging along a path of over 200 m

Traditional approaches to mobile robot navigation are quite different to what we understand of insect approaches. Robots commonly estimate their current metric position and destination position in a global reference frame, and plan the path between the two. Unfortunately, this approach tends to be fragile (Austin and Kouzoubov, 2002), depending upon global metric localisation, and requires considerable computation, especially compared to insect approaches. The above simple, biologically-motivated models have recently been investigated for mobile robot homing (Möller, 2000; Möller and Lambrinos, 2000), with encouraging results. A further motivation for implementing biologically-motivated approaches is to gain insight or to hypothesise about the internal mechanisms of biological systems. We will expand on this theme in the discussion in Section 6.

The average landmark vector model uses a unit vector to denote the bearing information of each landmark. The average landmark vector is formed by averaging the unit vectors pointing towards each landmark. The average landmark vector at the homing position is stored and used while homing. The stored vector is repeatedly compared with the current average landmark vector, and the difference results in a velocity vector. This velocity vector has been proven to give stable convergence to the home position (Lambrinos et al., 2000). An improved average landmark vector model (IALV) was proposed (Usher et al., 2002a, 2002b), which employs the bearing feature as well as range information (which is absent from the original ALV model). This model was used to drive an experimental mobile tractor (Usher et al., 2002a, 2002b), demonstrating that the IALV model can be used for successful homing. However, the IALV model requires the use of a compass to estimate the vectors to the landmarks in the global reference frame.

Previously, the authors have used a variation of the average landmark vector model, with a focus on trajectory shaping for docking (Wei et al., 2003, 2004). In docking, we wish to control the final orientation, as well as the position. The average landmark vector model (as well as the IALV model) offers weak control over the final orientation and
little or no control over the direction of approach. By contrast, the previous work by the authors (Wei et al., 2003, 2004), exploited the singularity near a landmark to create a directional ‘valley’ in the cost function, which ensured strong control over approach direction and final orientation. This is most appropriate for docking and achieves high accuracy (≈1 cm). However, a weakness of this approach is that, for starting conditions behind the docking station, trajectories can require sharp turns that the robot cannot execute.

Hence, we extend the previous work (Wei et al., 2003, 2004) to a weighted landmark vector model, which permits changes to the contributing weights of landmarks so that more control can be exerted over the trajectory shape. The basic idea is to initially draw the robot to the centre of the room and then switch to the final docking set of weights once the robot is in a more appropriate starting position. Section 2 briefly analyses the properties of the average landmark vector model, followed by a discussion of relevant cost functions in Section 3. Section 4 describes the weighted landmark vector model and the proposed control design and analysis. Finally, Section 5 presents simulated results for the weighted landmark vector model.

2 System model

The kinematic model for the mobile robot dynamics considered throughout this paper is that of a non-holonomic unicycle (Casalino et al., 1994). Let \( \langle g \rangle \) denote the global frame and \( \xi(t) = (x, y)^T \) denote the position of the unicycle in \( \langle g \rangle \). The orientation of the unicycle, \( \theta \), is given by the angle between the vehicle direction and the \( x \)-axis of \( \langle g \rangle \). The kinematics of the unicycle are

\[
\begin{align*}
\dot{x} &= u \cos \theta \\
\dot{y} &= u \sin \theta \\
\dot{\theta} &= \omega
\end{align*}
\]

where \( u \) is the linear velocity of the vehicle and \( \omega \) is its angular velocity (Figure 2).

**Figure 2** Model of unicycle-like vehicles. Frame \( \langle g \rangle \) is a global, fixed frame while \( \langle b \rangle \) is attached to the body of the robot.
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The linear velocity of the vehicle is denoted \( v = u(\cos(\theta), \sin(\theta)) \). It is useful to consider the related holonomic kinematics

\[
\begin{aligned}
\dot{x} &= v \\
\dot{\theta} &= \omega
\end{aligned}
\]  

(2)

where \( v \in \mathbb{R}^2 \) is an arbitrary velocity input in the global frame. Most of the initial work in the field of average landmark vectors has been implemented for holonomic control of mobile robots.

2.1 Average landmark vector model

The sensor information available to the mobile platform consists solely of bearing angles to landmarks in the environment that can be identified by the mobile platforms sensor systems, measured relative to a body-fixed reference frame. In the experimental work discussed in Section 5 we use a panoramic camera to determine bearings to visual targets. A landmark vector is defined as the unit vector pointing in the direction of a landmark, expressed in the body-fixed frame of the robot mobile platform (Lambrinos et al., 2000; Möller, 2000; Hamel and Mahony, 2000, 2002). Suppose that in the fixed, global frame \( \langle g \rangle \) there are \( n \), \((n \geq 3) \) landmark points \( \xi_i = (x_i, y_i) \), \((i = 1, 2, \ldots, n) \). Assume additionally that the landmark points are not co-linear. Let \( \langle b \rangle \) denote the body-fixed frame, which is attached to the vehicle with its x-axis aligned in the direction of robot motion and its origin at the reference point \( \xi(x, y) \) (Figure 2). In \( \langle b \rangle \) the landmark bearings are expressed as unit vectors:

\[
 p_i(\xi, \theta) = R(\theta)^T\frac{(\xi_i - \xi)}{|\xi_i - \xi|}
\]

(3)

where \( R(\theta) \) is the rotation from \( \langle b \rangle \) to \( \langle g \rangle \) defining the orientation of the unicycle

\[
 R(\theta) = \begin{bmatrix}
 \cos(\theta) & -\sin(\theta) \\
 \sin(\theta) & \cos(\theta)
\end{bmatrix}.
\]

(4)

Note that the observed landmarks in \( \langle b \rangle \) are a function of the state \((\xi, \theta)\) of the unicycle. Also, note that the landmarks are observed by the robot and therefore naturally appear in the body-fixed frame, rather than the global frame.

Since the landmarks are expressed in the body-fixed frame, they inherit dynamics from the ego-motion of the unicycle. The linear velocity \((u, 0)^T\) does not depend on the orientation \( \theta \) since the dynamics for \( p_i(\xi, \theta) \) are written in the body-fixed frame \( \langle b \rangle \). One has

\[
 p_i(\xi, \theta) = \begin{bmatrix}
 0 \\
 -\omega
\end{bmatrix} p_i - \frac{(I_2 - p_ip_i^T)}{|\xi_i - \xi|^2} u,
\]

(5)

The average landmark vector (ALV) is defined to be (Möller, 2000)

\[
 q = q(\xi, \theta) := \sum_{i=1}^{n} p_i(\xi, \theta).
\]

(6)
We use the notation developed in the parallel work by Hamel and Mahony (2000, 2002) for image-based visual servo-control of flying robotic systems. The kinematics of the ALV are given by

\[ \dot{q} = \alpha A^T q - Qv_b \]  

where

\[ A = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}, \quad Q = \sum_{i=1}^n \left( \frac{u_i p_i - p_i^T}{|\xi_i - \xi|} \right), \quad v_b = \begin{pmatrix} u \\ 0 \end{pmatrix} \]  

The ALV is expressed naturally in the body-fixed frame of the mobile platform. It is convenient to introduce a global frame representation \( q_g \) of \( q \) in the analysis of landmark feature vector properties. By construction, \( q_g \) is independent of the orientation of the unicycle and only depends on the relative position of the landmarks to the vehicle. Hence,

\[ \begin{align*}  
P_{g_i}(\xi) &= R(\theta) p_i(\xi, \theta) = \frac{\xi - \xi_i}{|\xi_i - \xi|} \\  
q_{g} &= \sum_{i=1}^n P_{g_i}(\xi) \end{align*} \]  

The kinematics of \( q_g \) are

\[ \begin{align*}  
\dot{q}_g &= -Q(\xi)v \\  
D_2 q_g &= -Q(\xi) \end{align*} \]  

where

\[ v = \xi \begin{pmatrix} u \cos(\theta) \\ u \sin(\theta) \end{pmatrix} \]  

is the velocity vector of the vehicle in the global frame. Note that \( Q(\xi) \) is independent of the orientation of the robot.

### 3 Cost functions

Following Möller (2000) we define a potential function on Cartesian space by

\[ U(\xi) = \sum_{i=1}^n \frac{|\xi - \xi_i|}{|\xi_i - \xi|} \]  

The function \( U(\xi) \) is continuous but not always differentiable on \( \mathbb{R}^n \). In particular, the derivatives of \( U(\xi) \) are not defined at landmark points \( \xi_i \). Nevertheless, it is easily verified that, for non-collinear target ensembles, \( U(\xi) \) is a strictly convex function and consequently has a unique global minimum. When well defined, the differential of \( U(\xi) \) is given by
The potential function $U(\xi)$ provides a powerful tool in analysing the performance of a stabilising control based on the landmark feature vector $q$ (Möller, 2000). However, in order to compute the potential, one requires knowledge of the landmark range relative to the frame of reference of the robot. This information that is not available to an on-line control algorithm without resort to a compass. It is convenient to introduce a cost function $\phi(\xi)$ that can be computed directly from visual information:

$$\phi(\xi) = [q(q, \theta)]^2 = q^T g = (q_g)^T q_g, \quad \xi \in \{\xi_i\}. \quad (14)$$

By construction $\phi(\xi)$ is independent of the orientation of the robot. It can also be written in terms of the derivative for $\xi$ of the proposed potential function $U(\xi)$:

$$\phi(\xi) = [D_\xi U(\xi)]^2. \quad (15)$$

Recalling equations (13) and (10), one has

$$D_\xi \phi(\xi) = 2q_g^T D_\xi q_g = -2q_g^T Q$$

$$= -2q_g^T D_\xi^2 U(\xi)$$

when $\xi_i \neq \xi$. That is $Q(\xi) = D_\xi^2 U(\xi)$ is the Hessian of $U(\xi)$.

The structure of $\phi(\xi)$ is of considerable interest in the development of control algorithms for both the holonomic equation (2) and non-holonomic equation (1) system models. To provide a rigorous analysis we extend $\phi(\xi)$ to landmark points as follows

$$\phi(\xi_i) = \inf_{\xi \to \xi_i} \lim_{i \to \xi} \phi(\xi). \quad (16)$$

The cost $\phi$ is smooth on all points that $\xi \neq \xi_i$ and discontinuous at each landmark point $\xi_i$.

Figure 3 shows the differences between the level sets of the functions $\phi(\xi)$ and $U(\xi)$. Note that the level sets of $\phi(\xi)$ have a pronounced distortion close to each of the target points. This is due to the discontinuity in derivative of the cost $U(\xi)$ at these points. Although the discontinuous-nature of $\phi(\xi)$ adds to the technical complexity of the analysis, it is particularly helpful in docking. In Figure 3, the minimum point of the cost $U(\xi)$ (and of $\phi(\xi)$) is close to the topmost target point. It can be seen that the robot, which minimises the cost $\phi(\xi)$, will first converge to the valley associated with the stretched form of the level sets of $\phi(\xi)$ and then converge towards the minimum. Indeed, in the limit as the minimum approaches the target point the level set degenerates into a single direction. Consequently, the nature of the cost will naturally lead to a control algorithm that achieves both positioning and orientation control, since the direction of the trajectories leading in to the optimum will determine the orientation. This valley in $\phi(\xi)$ and the resultant trajectory shapes are particularly useful in designing control algorithms for docking manoeuvres.
4 Weighted landmark vector model

In the snapshot model and ALV-like models, the landmarks are labelled by unit vectors, assuming that all landmarks contribute equally to the final vector. It appears that this might not be true for visual navigation of insects (Collett et al., 2002; Lambrinos et al., 2000). Drawing inspiration from this, we propose that for visual homing of robots, one or several landmarks may be more interesting than others. The weighted landmark vector model permits adjustment of the weights of the landmarks as needed. Here, we consider the use of the time-varying weights for trajectory shaping. By changing the weights of landmarks, the orientation and norm of $q$ is changed. Consequently the shape of the cost function is controllable.

The proposed weighted landmark vector model inherits characteristics from the average landmark vector model. Both of them use only the bearing information of landmarks. From the panoramic camera image, the bearing of each landmark is determined, denoted by a unit vector $p_i$ pointing from the current location to the landmark location. Those unit vectors are then multiplied by the landmark weights $\alpha_i(t)$ (Figure 4). The weighted landmark vector $q(x, y)$ is then computed by summing all the landmark vectors $\alpha_i(t)p_i$

$$q := \sum_{i=1}^{n} \alpha_i(t)p_i(\xi, \theta)$$

where $\alpha_i(t)$ is the weight of feature of landmark $\xi$. The weights $\alpha_i(t)$ ($i = 1, ..., n$) form a (possibly time-varying) set of weights. The cost functions $U(\xi)$ and $\phi(\xi)$ are redefined using the weighted landmark vector as above.

Note that a requirement for the WLV model is that we can identify or distinguish between the landmarks. In practice, this is not overly burdensome as relatively few landmarks are used and, thus, identification is simple. For example, in our experiments with two-colour blobs, one of the targets is simply placed upside down to distinguish it from the others.
Diagrammatic explanation of the weighted landmark vector model. The direction to each landmark $\xi_i$ is represented by an associated unit vector $p_i$. The weighted landmark vector is then the weighted sum of the unit vectors, where each unit vector $p_i$ is weighted by $\alpha_i(t)$, a possibly time-varying weight function.

As previously (Wei et al., 2003, 2004), the following body-fixed frame control law is proposed:

$$v = q.$$  \hfill (18)

This simple control design has the property that the cost $\phi(\xi)$ decreases along solutions of the closed loop system. For implementation, the weighted landmark vector is computed each iteration and is applied directly as the vehicle control. Note that it is not necessary to use a compass to convert to the global frame, unlike the IALV model.

For fixed values of the weights, $\alpha_i(t)$, the weighted landmark vector model analysis proceeds much as in (Wei et al., 2004). The proofs can be extended in a straightforward fashion and are now given here.

4.1 Global minimum

**Lemma 4.1** [Lemma 3.2 in (Wei et al., 2004)]: Suppose that there are $n$ ($n \geq 3$) landmark points $\xi_i(x_i, y_i)$, ($i = 1, 2, \ldots, n$) that are not co-linear. Consider the potential function $U(\xi)$ and the error function and the cost function $\phi(\xi)$ on $\mathbb{R}^2$. Then:

- There exists a unique point $\xi_*$ in the convex hull of the set of landmarks $\{\xi_i\}$ such that
  $$U(\xi_*) = \min_{\xi \in \mathbb{R}^2} U(\xi).$$

- If $\xi_0 \neq \xi_i$, for $i = 1, \ldots, n$ then
  $$\phi(\xi_*) = 0$$

  and $\xi_*$ is a local minima of $\phi$. Note that $U(\xi_*) \neq 0$. 


• If $\xi_i \neq \xi_0$ for $i = 1, \ldots, n$ then

$$\begin{align*}
D_\xi U(\xi_*) &= 0, \\
D_\xi \phi(\xi_*) &= 0.
\end{align*}$$

• If $\xi_i \neq \xi_0$ for $i = 1, \ldots, n$ then

$$\begin{align*}
D_\xi^2 U(\xi_*) &= Q(\xi_*) > 0, \\
D_\xi^2 \phi(\xi_*) &= 2Q(\xi_*)^T Q(\xi_*) > 0.
\end{align*}$$

**Proof:** Part 1 follows directly from the convexity of $U(\xi)$. Given $\xi_i \neq \xi_0$ ($i = 1, \ldots, n$) then $U(\xi)$ is differentiable at $\xi_*$ and it is clear that $D_\xi U(\xi_*) = -q_g(\xi_*) = 0$. As a consequence $\phi(\xi_*) = 0$ and $D_\xi \phi(\xi_*) = -q_g(\xi_*)^T Q(\xi_*) = 0$. This proves parts 2 and 3.

To prove part 4, it is simply a matter of computing the second derivative of $U$ and $\phi$ at $\xi_*$

$$\begin{align*}
D_\xi^2 U(\xi_*)[\eta, \mu] &= -D_\xi(\eta^T q_g)[\mu] = \mu^T Q\eta \\
D_\xi^2 \phi(\xi_*)[\eta, \mu] &= -D_\xi(2q_g^T Q\eta)[\mu] = 2\mu^T Q\eta - 2\mu^T q_g^T (D_\xi Q(\mu))\eta.
\end{align*}$$

At $\xi_*, q_g(\xi_*) = 0$ and the result follows.

Note that with appropriate choice of weights, the global minimum can be arbitrarily positioned within the convex hull of the landmark positions.

### 4.2 Convergence

In order to prove a full convergence result it is necessary to show existence of the solutions of the closed-loop system. To deal with all points in the space we extend the vector field $q_g$ onto landmark points using a limiting argument, as in (Wei et al., 2004).

For a target point $\xi$, define

$$q_g(\xi) = \begin{cases} 
q_{g,\eta}(\xi) & \text{if } |q_{g,\eta}(\xi)| > 1 \\
0 & \text{if } |q_{g,\eta}(\xi)| \leq 1.
\end{cases}$$

(19)

Note that the vector field obtained in this manner is not continuous at landmark points.

**Lemma 4.2** [Lemma 4.1 in (Wei et al., 2004)]: Suppose that there are $n$, ($n \geq 3$) landmark points. Let $\xi_*$ denote the global minimum of $\phi(\xi)$ (cf. Lemma 4.1) and $H$ the convex hull of the set of landmark points. Let $\xi(t)$ denote the solution to

$$\dot{\xi} = q_g(\xi)$$

where $q_g$ is given by equations (9) and (19). For any initial condition $\xi_0 \in \mathbb{R}^2$:
The solution $\xi(t)$ exists $\forall t > 0$ and $\xi(t) \in H$.

The solution $\xi(t)$ is asymptotically stable to $\xi_*$. That is, $\xi(t) \to \xi_*$ as $t \to \infty$.

If $\xi_*$ is not a landmark point, the solution $\xi(t)$ is locally exponentially stable to $\xi_*$. That is,

$$
\exists \delta, \sigma, \rho > 0, \ \forall \xi_0 \in H, \ |\xi_0 - \xi_*| < \delta, \ |\xi(t) - \xi_*| \leq \rho e^{-\sigma t}.
$$

The proof for the weighted landmark vector is a straightforward extension of the proof contained in (Wei et al., 2004).

4.3 Weight switching

As outlined above, the extension of the earlier work presented in (Wei et al., 2004) to weighted targets is quite straightforward. Now we wish to extend to time-varying weights, in order to achieve desirable docking trajectories. Clearly, for arbitrary time-varying weights, we cannot guarantee convergence. However, we can propose a weight-switching regime where an initial set of weights draws the robot to the centre of the room and the second set is used for docking. Given Lemmas 4.1 and 4.2 above, we know that the trajectories are convergent for each phase of this two phase scheme. In practice, we wish to vary the weights in a continuous manner to achieve smooth trajectories that are easier for the robot to follow. It is also intuitively clear that, for trajectories well away from target points and relatively short switching times, the resultant trajectories will be well-behaved.

5 Simulations and experiments

5.1 Landmark weights

To control trajectory shape, as well as the final homing orientation of the robot, a time varying weight strategy is proposed. Define $\alpha_{i,j}$ ($i = 1, \ldots, n$) as the $j$th weight set of the landmarks. Initially, the mobile robot will be driven towards the middle of the convex hull using the first weight set $\alpha_{1,1}$. Then, once the robot has been centred and is in a good position to complete the docking manoeuvre, a second set of weights, $\alpha_{1,2}$, is phased in. The second set of weights is designed to drive the robot to the docking position. Mathematically, we write

$$
q_i(t) = \sum_{j=1}^{n} \alpha_{i,j}(t)p_j
$$

$$
\alpha_{i,j} = \alpha_{i,1}(1 - \Delta(t)) + \alpha_{i,2}\Delta(t)
$$
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\[ \Delta(t) = \begin{cases} 
0, & t < t_0 \\
\frac{t-t_0}{T_{\text{switch}}}, & t_0 \leq t \leq (t_0 + T_{\text{switch}}) \\
1, & t > (t_0 + T_{\text{switch}}) 
\end{cases} \]  \tag{22}

where \( t_0 \) is the moment when \( q(t) = q_{\text{thresh}} \) and \( T_{\text{switch}} \) is the switching period. \( \alpha_{i,1} \) and \( \alpha_{i,2} \) are the sets of landmark weights in stage 1 \((t < t_0)\) and stage 2 \((t > t_0 + T_{\text{switch}})\), respectively. \( q_{\text{thresh}} \) is a threshold used to determine when to switch and \( q(t) \) is the same as defined in equation (17).

5.2 Simulations

Figures 5(a) and (b) show the effect of using constant (but unequal) weights. By appropriate selection of the weights, we can make the mobile robot converge to any location within the convex hull of the landmark points. In Figure 5(a), under the constant weight control law, the trajectories converged to a central position, far from landmark points. However, the orientation of the trajectories in the final positions is dependent on the starting position (this is because the orientation of our unicycle robot is determined by the final direction of travel). Figure 5(b) shows that, under another set of weights, trajectories converged to the docking position, which is close to landmark 3. The trajectories converge within a narrower orientation range, suitable for docking. Unfortunately, those trajectories coming from behind landmark 3 turn too sharply as they are very close to the docking position. This turn causes problems in controlling the final orientation and, furthermore, the robot may not be able to turn so sharply. This sharp turn has motivated the use of time-varying weights and the strategy of first moving the robot towards the centre of the room and then performing docking.

Figure 5

Simulations of trajectories using constant weights (the level sets of the cost function are also shown). (a) trajectories when using constant weight set of \([\alpha_1 = 0.7, \alpha_2 = 0.7, \alpha_3 = 0.4]\). The set of weights makes trajectories converge to a central zone of the convex hull. (b) simulated trajectories when using \([\alpha_1 = 1, \alpha_2 = 1, \alpha_3 = 1.25]\). The asterisks (*) in the figure denote the starting points of the trajectories. (These simulations use the same landmark configuration as that of the actual indoor experiments)
Figure 6 shows the simulation results employing the proposed weight-switching strategy. Initially, the trajectories all converge to a central zone, far from any landmark point. Then, using the proposed time-varying weight function, the second set of landmark weights is phased in smoothly. Finally, trajectories converge to the final docking position, using the second set of weights. Smooth trajectories can be seen from the simulations in Figure 6. The final orientation of trajectories distributed within a narrow angle range.

5.3 Experiments

To verify the weighted landmark vector model experimentally, it was implemented on the ANU XR4000 robot (see Figure 8(a)). Bi-colour targets are used for easy visual recognition, as can be seen in Figure 8(a). A panoramic camera (at the top of the robot in Figure 8(a)) is used to capture omni-directional images. An example image is shown in Figure 8(b). A relatively simple visual processing algorithm is then used to determine the positions of the blobs in the image. The blob positions then directly give the unit vectors representing the landmark directions (equation (3)). Note that no unwarping of the image is required and that no coordinate transformation is necessary, since the centre of the camera (and, hence, the centre of the image) is located at the robot coordinate frame (the centre of the robot). For further details of the image processing algorithm, see (Wei et al., 2003, 2004).

Figure 7 shows the experimental results for the proposed weighted landmark vector model. The same weights used for the simulations were used for the real experiments; initial set: $[\alpha_{1,1} = 0.7, \alpha_{2,1} = 0.7, \alpha_{3,1} = 0.4]$ and final set: $[\alpha_{1,2} = 1, \alpha_{2,2} = 1, \alpha_{3,2} = 1.25]$. The switching threshold used was $q_{\text{thresh}} = 0.06$ and the switching period used was $T_{\text{switch}} = 10$ seconds. The experimental results again demonstrate the initial convergence...
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To a central zone, followed by successful docking. Note that the simulated trajectories of Figure 6 are in close agreement to the experimental results of Figure 7.

Figure 7  Experimental results showing the trajectories for 20 executions of the two-phase approach to docking, from different starting poses. Note how the robot is pulled to the centre of the room initially and then switches to the docking phase.

![Figure 7](image)

Figure 8  (a) ANU XR4000 robot used for the experiments, with omni-directional camera on top and (b) an example image from the omni-directional camera.

![Figure 8](image)

Figure 9 shows a close up of the final poses and orientations that the robot achieved. The standard deviation in the final poses of the robot is 0.22 cm in the global x direction, 0.65 cm in the y direction and 2.6° in orientation. The deviation in the x direction is slightly less than, and the deviation in orientation is significantly less than the constant weight experimental results achieved previously (Wei et al., 2004). In Wei et al. (2004), the x standard deviation is 0.38 cm and the orientation standard deviation is 6.4°. The improved docking accuracy can be explained by the better starting positions for the final docking phase.
In summary, both the simulated trajectories and experimental results demonstrate the effectiveness of the proposed weight-switching method in achieving high accuracy docking from a wide range of initial conditions. The experimental results are particularly impressive, given that a low-cost and relatively inaccurate panoramic camera is used as the sensor.

6 Discussion and conclusions

In this paper, a novel Weighted Landmark Vector model was proposed. It is derived from biomimetic models of visual navigation in insects. Using the weighted landmark vector model, a control algorithm for mobile robots was developed. Simulation and experimental results demonstrate the power of the weighted landmark vector model, in that it allows shaping the trajectories that the robot follows. Here, we have avoided the sharp turns near the docking station (Figure 5(b)), while converging with the final docking position and orientation well controlled. In fact, the proposed method achieves better docking accuracy than previous works.

Note that, despite the complexity of the analysis in Sections 3 and 4 above and in (Wei et al., 2003, 2004), the implementation of both the average landmark vector model and the weighted landmark vector model is straightforward, requiring little computation. In fact, with the use of the panoramic camera, there are not even any coordinate
transformations required. Perhaps the low computational requirements are unsurprising since the approach has been inspired by the apparently similar models used by ants (Wehner, 2003) and bees (Collett et al., 2002; Cartwright and Collett, 1983). However, it is gratifying to be able to prove mathematically and experimentally that a biomimetic model is applicable to man-made systems, such as robots.

One interesting outcome of the weighted landmark vector model is that it permits arbitrary positioning of the global minimum within the convex hull of the landmark points. Thus, the use of weighted landmarks allows for use of natural landmarks for convergence to an arbitrary position. However, note that the valley we exploited here for docking exists only in the vicinity of target points. Nevertheless, with a rich set of natural landmarks (such as may be found in natural scenes), one can imagine convergence or docking to arbitrary positions.

One final aspect of the results presented in this paper is the information that may be inferred about biological systems from the artificial experiments conducted here. The possibility of this type of inference is an interesting aspect of biomimetic robotics and permits development of hypotheses about biological systems, which are impractical to test in other ways. One such hypothesis, arising from this work, is the theory that biological systems may use a similar scheme of time-varying weights for navigation over long distances where a single set of landmarks is not suitable. When navigating over longer distances, multiple sets of landmarks are necessary due to range limitations on sensors (usually visual resolution limits). It appears that bees rely on sequential sets of landmarks for long-distance navigation (Menzel et al., 1996). Given the similarities between the average landmark vector model and the observed behaviours of bees, it is possible that bees use a method similar to the weighted landmark vector model proposed here for switching between sets of landmarks. Unfortunately, experiments to prove or disprove this hypothesis with any degree of confidence are likely to be infeasible. However, the simplicity of the weighted landmark vector model is appealing and the experimental demonstration with the robot supports this hypothesis.

Acknowledgements

This work was supported by funding from National ICT Australia. National ICT Australia is funded by the Australian Government’s Department of Communications, Information Technology and the Arts and the Australian Research Council through Backing Australia’s Ability and the ICT Centre of Excellence programme.

References


