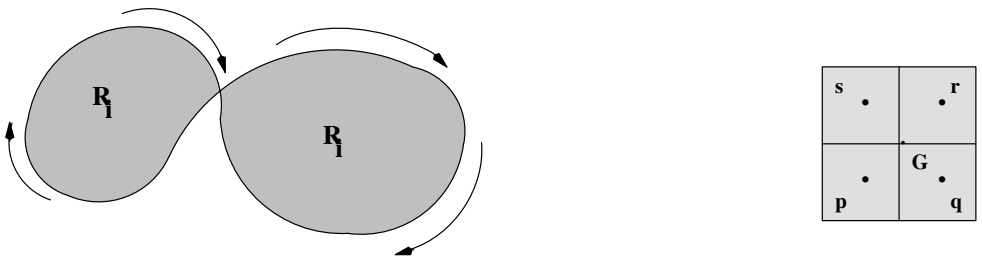
tion (i) ensures that the boundary is not lost while it is followed and condition (ii) restrain from moving back along the path.

Grid points with $C_c = 5$ and 10, called as the crossing points, give rise to difficulties in the direction of movement. This can be solved in different ways depending upon the class of the boundary followed. For example, in the case of objects with simple crossover points like the one shown in figure A.3a, the new direction code is nothing but the old direction code incremented by one. When previous $C_d = 3$, the new code is taken as 0. For a digitized object, the angular change at each grid point is always 0, 90 degrees or –90 degrees.

The minimum number of descriptors needed for classification depends upon the complexity of the image and accuracy needed. The first 15 values of the Fourier descriptors were used for the classification.

The parameters $\Delta\phi_n$ and l_n associated with each vertex point on the object boundary can be estimated by following the boundary in clockwise or anticlockwise direction. In our studies we use the scheme proposed by Sidhu *et al.*[139] to follow the boundary points of an object. The boundary is followed by keeping the inside region of the object (R_i in Fig.A.3a) always to the right side of the path. The direction of following at each boundary point is determined using the 'containment' and 'direction' codes at that point. They are found as follows:



(a) (b)

Figure A.3 Following of the boundary of a simple closed curve

Consider a boundary point G (which is same as the grid point) as shown in figure A.3b. In figure A.3b, p, q, r and s are the four neighboring grids and i_p, i_q, i_r and i_s, their grid values. Let the grid value is '1' if it is inside the object and '0' if it is outside. The 'containment code' at G, $C_c = (i_p, i_q, i_r, i_s)_2 = i_p + 2i_q + 4i_r + 8i_s$. There are 16 possible canonical forms and it could be seen that for every grid point G on the boundary with $C_c \neq 5$ and $C_c \neq 10$, there is exactly one neighboring boundary point G' satisfying the following two conditions: (i) G' is on the boundary and (ii) when moving from G to G' we can keep the inside region of the image to the right. The direction in which the boundary can be followed by moving from G to G' is only a function of the containment code at point G. The directions and codes taken here are: 0–>right, 1–>up, 2–>left and 3–>down. It is to be pointed out that the above condi-

$$A_k = \sqrt{a_k^2 + b_k^2} \tag{A.0}$$

$$\lambda_k = tan^{-1}(\frac{b_k}{a_k}) \tag{A.1}$$

For a polygonal curve having m vertices $V_0, V_1, \ldots V_m$ (see figure A.2), the Fourier descriptors could be calculated using the following set of equations[89],

$$a_k = -\frac{1}{k\pi}\sum_{n=1}^{m} \Delta\phi_n sin\frac{2\pi k l_n}{L} \tag{A.2}$$

$$b_k = \frac{1}{k\pi}\sum_{n=1}^{m} \Delta\phi_n cos\frac{2\pi k l_n}{L} \tag{A.3}$$

where

$$l_n = \sum_{i=1}^{n} \Delta l_i \tag{A.4}$$

Δl_i is the length of the edge (V_{i-1}, V_i) and $\Delta\phi_n$, the change in angular direction at V_n.

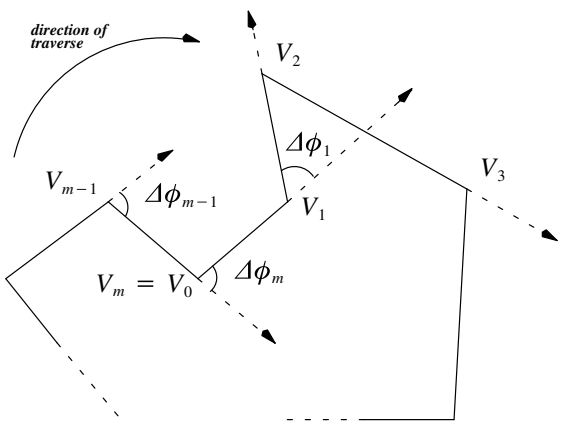


Figure A.2 Description of a polygonal curve

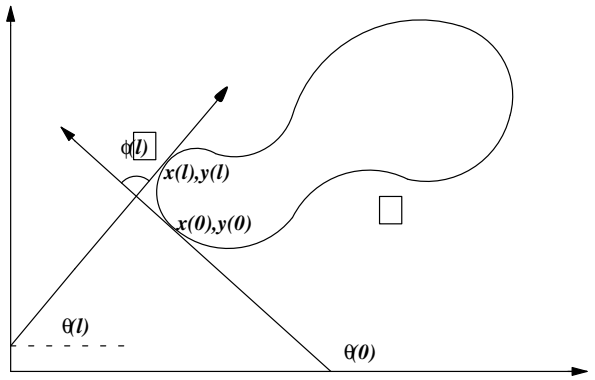


Figure A.1 Representation of a plane curve. θ(l) is the tangential direction distance l and φ(l) the cumulative angular bend

Normalizing the function with respect to length,

$$\phi^*(t) = \phi(\frac{Lt}{2\pi}) + t \qquad \text{(A.–3)}$$

where t ranges from 0 to 2π. $\phi^*(t)$ is invariant under translation, rotation and scale changes#. Expanding $\phi^*(t)$ as a Fourier series,

$$\phi^*(t) = \mu_0 + \sum_{k=1}^{\infty}(\alpha_k \cos kt + b_k \sin kt) \qquad \text{(A.–2)}$$

In polar form the above expression becomes,

$$\phi^*(t) = a_0 + \sum_{k=1}^{\infty} A_k \cos(kt - \lambda_k) \qquad \text{(A.–1)}$$

The set $\{A_k, \lambda_{k,\, k=1,..\infty}\}$ is defined as the Fourier descriptors for the curve γ; where

---

$\phi^*(t) = 0$ for a circle

APPENDIX A.

FOURIER DESCRIPTORS

In many object recognition problems, information about the object boundary alone is sufficient for successful classification. Two such examples are, hand written character recognition and the assembly line vision system. Fourier Descriptors[89][90] provide a powerful technique to describe boundaries for non–overlapping objects. The descriptors are defined as follows:

Consider a simple closed curve γ with parametric representation $(x(l),y(l)=z(l))$ where l is the arc length $0 \leq l \leq L$. Denoting the angular direction at the point l by a function $\theta(l)$, we can generate a function $\phi(l)$ which is the cumulative angular bend between the starting point and point l (see Fig.1), defined as $\phi(l) = \theta(l) - \theta(0)$. For a clockwise orientation $\phi(L)=-2\pi$.

of an AUV using elevators. The fuzzy controller, called the premature controller, is used as a start–up controller till the neural network controller learns the the vehicle characteristics. There is a specific learning phase in their control scheme which necessitates the premature controller. The studies presented on this 'indirect control scheme' are rather limited

imprecise models and parameter variations, the design process needs raw estimation of the parameters.

The emergence of neural networks(NN) as effective learning systems for a wide variety of applications has resulted in the use of these networks as adaptive controllers. The dynamics of the controlled system(plant) need not be known for the design of these controllers. This is a very desirable feature in the design of an underwater vehicle control system. Also the ability of these networks for adaptation and disturbance rejection as well as their highly parallel nature of computation enable them to be better candidates for control applications. The areas of neural network applications as controllers include robotics, autonomous land and underwater vehicles and chemical processes.

A neural network based control scheme for URVs is described by Yuh in [143]. The direct control scheme is used with the error backpropagation[14] as the learning algorithm. Using a three layer network good trajectory tracking is achieved for vehicle. The error at the output of the neural network, which is needed for training, is estimated from the plant output error similar to the specialized learning scheme described in [52]. Some results dealing with issues such as robustness of the controller towards parameter and environmental disturbances are also presented. Sanner and Akin[151] discuss a real–time single axis attitude regulation of an underwater tele–robot using a neural network of three layers. The paper deals with some of the practical implementation issues and indicates that a single serial microprocessor implementation of the neural network controller may be impossible.

The control schemes discussed above are generally for remotely operated vehicles with comparable velocities along all the axes and the motion along each direction is controlled by separate thrusters. The problem of controlling the vehicle is more complicated when control surfaces are used rather than thrusters. Fujii and Ura[138] presents one of the first implementation of a combination of a fuzzy controller and neural network for the pitch control

Even though the technology for Autonomous Land Vehicles(ALV) is already in an advanced stage it cannot be directly adopted for the AUVs because of the highly uncertain nature of the ocean environment, the partially known vehicle dynamics and the additional degrees of freedom present. Conventional controllers are inadequate for such tasks, as they provide the robustness only over a small range and the complete dynamics of the vehicle should be known precisely for their design. Since the exact hydrodynamic characteristics of the vehicle is known only after its design, the development of a conventional controller involves exhaustive and expensive testing of the vehicle. This necessitates the implementation of an intelligent, adaptive controller for effective and efficient operation of the AUVs. The highly uncertain nature of the ocean environment and the nonlinear nature of the vehicle dynamics arising from the rigid body coupling and the external forces due to ocean current etc., make the design of an AUV control system a significant challenge.

In recent years, several control strategies have been discussed for the application in underwater robotic vehicles, especially ROVs. Goheen *et al.*[140] describes a supervisory control scheme for ROVs implemented in a hierarchical way. The higher level controllers monitor the performance of the lower level controllers and often assist the control action. The lower level controllers are nothing but a series of single–input single–output controllers. Some of the recent studies with this scheme for the velocity control by manipulating the thrusters is presented in [141] . The overall tracking performance of the controllers described improves as time proceeds but the initial overshoot in most cases is large.

Yoerger and Slotine[142] discuss a sliding mode control scheme for underwater vehicles by splitting the vehicle dynamics into a series of single–input single–output relationships. The simulation studies are done on the University of New Hampshire *EAVE* vehicle dynamics. The main advantage of their method is that it can deal with the nonlinear vehicle dynamics directly without the need for its piecewise linearization. Although the method is robust to

APPENDIX B

CONTROL SCHEMES FOR UNDERWATER VEHICLES

Oceanographic exploration is one of the fast emerging applications of robotics. Since a vast region of the ocean is still unexplored because of the difficulties in having manned interventions, robotics is the most suitable alternative. The design of an underwater robotic system is more challenging than a land or space based one. Current vehicles such as Remotely Operated Vehicles(ROV) and Unmanned Underwater Vehicles(UUV) are not fully autonomous and a large variety of their control actions need human involvement. This restricts their operating regime and effectiveness. Autonomous Underwater Vehicles (AUVs) are the next generation vehicles in ocean robotics and have become an intense area of research in recent years because of their commercial as well as military potential and the technological challenge in developing them. The possible commercial applications of AUVs include coastal and offshore structure inspection, recovery, cable laying, geographical and arctic surveys. They can be used for a number of military applications such as early warning, intelligence gathering, mining and mine countermeasures.

$$
\begin{aligned}
\Sigma M_N \;=\;& 0.5\rho l^5[N'_{r'}r' + N'_{p'}p' + N'_{pq}pq] \\
&+\; 0.5\rho l^4[N'_p up + N'_r ur + N_{v'}v'] \\
&+ 0.5\,\rho l^3[N'_* u^2 + N'_v uv + N'_{v|v|}\, v\sqrt{(v^2 + w^2)}] \\
&+ 0.5\,\rho l^3[N'_{\delta r} u^2\delta_r + N'_{\delta r\eta} u^2\delta_r\,[\eta - 1/C]C\,] \\
&- 0.5\,C_d \int_l xh(x)v(x)\sqrt{v^2(x) + w^2(x)}\,dx \\
&- 0.5\rho l\overline{C}_L \int_{x_2}^{x_1} xw(x)\overline{v}_{FW}(t - \tau[x])dx
\end{aligned}
\tag{C.9}
$$

Refer to [95][96] for details on notations.

$$- 0.5\ C_d \int_l (b(x)w(x)\sqrt{v^2(x) + w^2(x)}\,dx$$

$$- 0.5\rho l\ \overline{C}_L \int_{x_2}^{x_1} v(x)\overline{v}_{FW}(t - \tau[x])dx \tag{C.6}$$

Rolling moment:

$$\begin{aligned}
\Sigma M_K = \quad & 0.5\rho l^5[K'_{p'}p' + K'_{r'}r' + K'_{qr}qr + K'_{p|p|}p|p|] \\
& + \ 0.5\rho l^4[K'_p up + K'_r ur + K'_{v'}v' + K'_{wp}wp] \\
& + 0.5\ \rho l^3[K'_* u^2 + K'_{vR}\ uv + K'_i\ u\ v_{FW}\ (t - \tau_r)] \\
& + 0.5\rho l^2[K'_{\delta_r} u^2\delta_r + K'_{\delta_r\eta} u^2\delta_r\ [\eta - 1/C]C\ ] \\
& + 0.5\rho l^3(u^2 + v_s{}^2 + w_s{}^2)\ \beta_s{}^2[K'_{4s}sin4\phi s + K'_{8s}sin8\phi s] \\
& + 0.5\rho l^2 z_d\ \overline{C}_L \int_{x_2}^{x_1} w(x)\overline{v}_{FW}(t - \tau[x])dx
\end{aligned} \tag{C.7}$$

Pitching momrnt:

$$\begin{aligned}
\Sigma M_M = \ & 0.5\rho l^5[M'_{q'}q' + M'_{rp}rp] \\
& + 0.5\rho l^4[M'_{w'}w' + M'_q uq] \\
& + 0.5\ \rho l^3[M'_* u^2 + M'_w uw + M'_{w|w|}\ w\sqrt{(v^2 + w^2)}] \\
& + 0.5\ \rho l^3[M'_{|w|}u|w| + M'_{ww}\ \sqrt{|w(v^2 + w^2)|}] \\
& + 0.5\ \rho l^3[M'_{\delta_s} u^2\delta_s + M'_{\delta_s\eta} u^2\delta_s\ [\eta - 1/C]C\ ] \\
& + 0.5\ C_d \int_l xb(x)w(x)\sqrt{v^2(x) + w^2(x)}\,dx \\
& - 0.5\rho l_l\ \overline{C}_L \int_{x_2}^{x_1} xv(x)\overline{v}_{FW}(t - \tau[x])dx
\end{aligned} \tag{C.8}$$

Yawing moment:

where,

Axial Force:

$$\begin{aligned}\Sigma F_x = \quad & 0.5\rho l^4 \, (X_{qq} \, q^2 + X'_{rr} r^2 + X'_{rp} rp) \\ & + 0.5 \, \rho l^3 \, (X'_{u'} u' + X'_{vr} vr + X'_{wq} wq) \\ & + 0.5 \, \rho l^2 (X'_{vv} v^2 + X'_{ww} w^2) \\ & + 0.5 \, \rho l^2 \, (X'_{\delta_r \delta_r} u^2 \delta_r^{\,2} + X'_{\delta_s \delta_s} u^2 \delta_s^{\,2}) \end{aligned} \tag{C.4}$$

Lateral Force:

$$\begin{aligned}\Sigma F_y = \quad & 0.5\rho l^4 [Y'_{r'} \, r' + Y'_{p'} \, p' + Y'_{p|p|} \, p|p| + Y'_{pq} pq] \\ & + 0.5 \, \rho l^3 [Y'_r ur + Y'_p up + Y'_{v'} v' + Y'_{wp} wp] \\ & + 0.5\rho l^2 [Y'_* \, u^2 + Y'_v uv + Y'_{v|v|R} \, v\sqrt{v^2 + w^2}] \\ & + 0.5\rho l^2 [Y'_{\delta_r} u^2 \delta_r + Y'_{\delta_r \eta} u^2 \delta_r \, [\eta - 1/C] C \,] \\ & - 0.5 \, C_d \int_l (h(x) v(x) \sqrt{v^2(x) + w^2(x)} \, dx \\ & - 0.5\rho l \, \overline{C}_L \int_{x_2}^{x_1} w(x) \overline{v}_{FW} (t - \tau[x]) dx \end{aligned} \tag{C.5}$$

Normal force:

$$\begin{aligned}\Sigma F_z = \quad & 0.5\rho l^4 Z'_{q'} q' \\ & + 0.5 \, \rho l^3 [Z'_{w'} w' + Z'_q uq + Z'_{vp} vp] \\ & + 0.5 \, \rho l^2 [Z'_* \, u^2 + Z'_w uw] \\ & + [Z'_{|w|} u|w| + Z'_{ww} \sqrt{|w(v^2 + w^2)|}] \\ & + [Z'_{\delta_s} u^2 \delta_s + z'_{\delta_s \eta} u^2 \delta_s \, [\eta - 1/C] C \,] \end{aligned}$$

APPENDIX C.

NONLINEAR EQUATIONS OF MOTION FOR THE AUV

Following are the equations of motion for the 'Ocean Voyager', used in the simulation studies.

$$m[u' - vr + wq - x_G(q^2 + r^2) + y_G(pq - r') + z_G(pr + q') = \Sigma F_x \qquad \text{(C.–2)}$$

$$m[v' - wp + ur - y_G(r^2 + p^2) + z_G(qr - p') + x_G(qp + r') = \Sigma F_y \qquad \text{(C.–1)}$$

$$m[w' - uq + vp - z_G(p^2 + q^2) + x_G(rp - q') + y_G(rq + p') = \Sigma F_z \qquad \text{(C.0)}$$

$$I_x p' + (I_z - I_y)qr - (r' + pq)I_{xz} + (r^2 - q^2)I_{yz} + (pr - q')I_{xy} + m[y_G(w' - uq + vp) - z_G(v' - wp + ur)] = \Sigma M_K \qquad \text{(C.1)}$$

$$I_y q' + (I_x - I_z)rp - (p' + qr)I_{xy} + (p^2 - r^2)I_{xz} + (qp - r')I_{yz} + m[z_G(u' - vr + wq) - x_G(w' - uq + vp)] = \Sigma M_M \qquad \text{(C.2)}$$

$$I_z r' + (I_y - I_x)pq - (q' + rp)I_{yz} + (q^2 - p^2)I_{xy} + (rq - p')I_{xz} + m[x_G(v - wp + ur) - y_G(u' vr + wq)] = \Sigma M_N \qquad \text{(C.3)}$$

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