MULTI-SENSOR DATA FUSION FOR SITUATIONAL ASSESSMENT - A CRITICAL ELEMENT OF SYSTEMS INTEGRATION, SOME THEORY AND APPLICATION TO COLLISION AVOIDANCE

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1. Introduction

To achieve systems integration[1] for large complex engineering systems, which incorporate many disparate technologies/methodologies, any viable approach must exhibit a set of *quality* features such as interoperability, extensibility, robustness and survivability, modularity and portability, ... Which in turn require at least three fundamental elements

- architectures for integration,
- open system for communications and construction,
- object oriented technology for components definition.

System architectures take many forms - such as the *hierarchical* or functional multi-layered approaches (including NASREM, RC3, IMA-ARNIC 651, ...) or fully distributed-decentralised flat *subsumption* architectures. The hierarchical architecture[2] based on the Stimulus Hypothesis Response (SHORE) paradigm is most popular in which the

- *Stimulus* part relates to sensor processing, data fusion and picture compilation aspects
- *Hypothesis* part relates to situational assessment, diagnositics monitoring aspect
- *Response* part relates to the planning, decisioning and control aspect.

In this paper we consider only the level 1 or layer 1 aspect, Multi Sensor Data Fusion (MSDF) for situational assessment for real time complex processes. All three elements of the SHORE paradigm have been considered by the ISIS group for demonstrating this architecture for systems integration of a fully autonomous road, cross-country and drilling vehicle on CEC Project Panorama. MSDF is a "continuous process dealing with the association correlation, and combination of data and information from multiple disparate sources to achieve a refined state estimate about the environment and timely assessment of the pituation". Here we only consider the processes of data integration and state estimation. To integrate data from disparate data sources such as sensors, look-up tables, human experiences/observations, data bases, etc a common currency of information content and data representation is required. Existing theories[3-5] such as Bayesian, Dempster-Shafer, Artificial Neural Networks (ANN), Case Based Reasoning, Method of Endorsement, Blackboard Expert Systems, Fuzzy Logic etc - all of which have been used for MSDF - are inadequate or inappropriate. We propose neurofuzzy algorithms[6], since they readily incorporate database knowledge/symbolic/linguistic knowledge in the form of fuzzy rules, and sensory data in a single environment/processor.

2. Neurofuzzy Algorithms

Neurofuzzy algorithms are single layer ANN, in which the input layer is composed of basis functions

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$a_i(\underline{x}(t))$ $(i = 1, \ p)$ defined over a lattice of the input data or measurements $\underline{x}(t) \in R^n \, (n << p)$, the output layer is a set of adjustable weights $\underline{w}(t)$, such that the network output $y = \underline{a}^T \underline{w}$; as the network is linear in the adjustable weights, linear algebraic methods and linear optimisation techniques can be used in training the network to learn some unknown nonlinear input/output mapping $y = f(\underline{x})$. These networks have provable learning convergence and stability conditions and are appropriate for *online* applications such as dynamic process modelling, control and estimation. Under certain conditions, these networks are input/output equivalent to a class of fuzzy systems with adjustable rule confidences thereby allowing *apriori* knowledge to be incorporated as well as representing linguistic/symbolic processes. A major deficiency of these networks, is that as *n* increases, the computation/memory cost increases exponentially (this applies to all rule base paradigms), however recent research[7] on neurofuzzy construction algorithms in ISIS, have shown that parsimonious models can be automatically generated. So now we are able to construct input/output models with very few parameters (or rules) for arbitrary nonlinear dynamical processes with either data or symbolic representations/inputs.

Given that the plant is dependent on some operating point process (e.g. Mach number, altitude for a gas turbine or aircraft dynamics) over the system envelop, then a quasi-linear ARMA model[8] can be found which is parameterised by an additive sum of neurofuzzy systems - each in turn with few parameters. This model has a state space representation which is cononical and directly amenable to Kalman filtering. In this regard ISIS has generated several neurofuzzy Kalman filters[9] for nonlinear state estimation of *unknown* dynamical processes with measurable/observable operating points. Given that for each data source there is an appropriate estimator/tracker, there is then the problem of data integration or fusion where the sensors refer to the same state entity. Here we adopt the distributed -decentralised fusion architecture[5], whereby each sensor contains its own independent estimator, sharing its results with all other relevant sensors (as additional post processing inputs). Fusion at each 'intelligent sensor', is based on a weighted sum of all sensor estimates e.g.

$\hat{\underline{x}} - \left(\sum_{i-1}^{r} \underline{p}_i^{-1} \hat{\underline{x}}_i \right) \left(\sum_{i=1}^{r} \underline{p}_i^{-1} \right)^{-1}$ where $\underline{p}_i$ = covariance of $\underline{x}_i$, $\hat{\underline{x}}_i$ is its estimate given by the ith sector.

3. Collision Avoidance

To illustrate this approach we consider the application[10] of these methods to the collision avoidance of helicopters in bad weather conditions (fog, heavy rain, snow storms, etc) when visual sensing is impossible. There are two subproblems:

(i) the *localisation problem.* Where is the aircraft in 3-D space, here GPS, INS, RADALT, ADS, sensors are available for estimation and fusion.

(ii) the *object detection and tracking* problem. Determination of fixed and moving obstacles in 3-D space, here TCAS, microwave radar, millimetric radar, and terrain data bases are available for estimation and fusion.

Additionally, subproblems such as safe navigation through this obstacle space to avoid collisions and the presentation of the pilot of safe flight corridors are relatively straight forward, e.g. use of potential field theory etc.

The demonstrator is a Westland Lynx helicopter flight simulator (based on 6 silicon graphic processors) with a 45 ft display screen, successful simulations including head on and crossing agile air obstacles over mountainous terrain have demonstrated the effacy of this methodology.

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