Attractor Dynamics to Fuse Strongly Perturbed Sensor Data

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Abstract—**We present a new approach to multi sensor fusion which is based on coupled nonlinear attractor dynamics. The state of the dynamics represents the fused estimate of a physical entity measured by multiple sensors. Each sensor-reading but also general expert knowledge about the measured system specifies a local stable fixed point (attractor) with a limited basin of attraction of the dynamics. The dynamic state variable converges to a global stable state which is the system's fused estimate. For the example of measuring the oil film thickness on seawater by means of multispectral radiometer measurements gathered during flights across a polluted area, we show that our approach is particularly useful for fusing multimodal strongly perturbed sensor data.**

I. Introduction

The aim of every fusion technique is to achieve improved accuracies and more specific inferences caused by the inherent redundancy provided by multiple sensors. A general overview about theoretical and application–oriented papers can be found in [1]. Multisensor environments typically generate a large amount of data based on sensors which often have different characteristics, gains, saturation levels and reliabilities. In addition, the sensor data are often corrupted by a variety of errors and perturbations which continually vary because of temporal changes in the environment. To deal with these problems, many different specific fusion techniques have been developed using fuzzy logic, neural nets, expert systems and other approaches [2]. We present a new, more general approach, which translates information about a measured physical quantity into the mathematical concept of nonlinear attractors. Within this approach information is not restricted to sensor data but can be any knowledge about the physical system. As an example of an application we deal with detecting oil films on seawater in order to determine their thickness.

II. Characteristics of the Sensor Data

The sensor data are acquired during flights across the polluted sea area using modern multi sensor technology [3]. In order to disperse oil spots successfully, their type, distribution and total volume have to be reliably determined.

The measurement principle is based on interactions of electromagnetic waves with different substances on the sea surface. The electromagnetic radiation is measured as intensities by several passive sensors such as a multispectral radiometer, infrared and ultraviolet sensors and active systems like laser fluorescence devices. The signals from these sensors are subject to perturbations like stochastic and systematic errors, caused by the physical measurement system. These are different calibration and saturation levels of the signals, temporal breakdowns of the sensors, white noise, isolated spikes due to electrical discharge causing outliers, etc. Furthermore, the physical model of the emission and backscattering mechanism [4] suggests ambiguous measurements of a sensor with a specific wavelength due to interference effects. To solve for these ambiguities, three microwave radiometers are used, operating at frequencies of 18, 36 and 89 GHz and having different geometrical resolutions because of different filter characteristics. The main problem of the sensor fusion system is to convert redundant and partially ambiguous information of the sensor signals into an accurate estimate of the oil thickness. Another problem is that no spatially resolved calibration measurements of the distributed oil spot are available.

In the following we show that our approach solves these problems by automatically converging to the estimate which makes the best compromise between all sensor measurements and additional knowledge about the system.

III. Nonlinear Attractor Dynamics

The basic idea behind our approach is to represent information about the measured physical system as local stable states or *attractors* of a nonlinear dynamical system [5]. This dynamics is solved by iterating the corresponding differential equation using the simple Euler method. Given that the parameters and the time scale of the dynamics are chosen appropriately, the state variable converges into a global stable state which results from a nonlinear superposition of all local attractors. This state then represents an estimate of the system's physical state.

We will describe the approach for the experimental setup described in the previous section. The physical quantity to estimate is the thickness $\tilde{d}(\vec{r}_i)$ of the oil film at the discretized spatial locations $\vec{r}_i = (x, y)_i$. Then the dynamical system for the estimate $d(\vec{r}_i)$ of $\tilde{d}$ has the form:

$$\tau \dot{d}(\vec{r}_i) = \sum_k \lambda_k F_i^{(k)} = \lambda_S F_i^{(S)} + \lambda_\epsilon F_i^{(\epsilon)} + \lambda_A F_i^{(A)} + \dots \quad (1)$$

Here $\dot{d}$ is the time derivative of the dynamic state variable and the $F_i^{(k)}$ are contributions to the sensor fusion process stemming from the sensor readings ($F_i^{(S)}$), the spatial interaction between neighbouring locations ($F_i^{(\epsilon)}$) and a priori knowledge about the thickness distribution ($F_i^{(A)}$). These contributions will be explained in detail later. The coefficients λ_k are the relative strengths of the contributions. The unified formulation of information as attractors allows for an easy extension of the dynamics by additional contributions $F_i^{(k)}$. The *time scale* τ controls how fast the state

[2]Supported by the German Federal Foundation for Environment

variable d can change. The only requirement is that the dynamics evolves on a faster time scale than the physical state which is measured by the sensors. In the example of the oil film we analyse the sensor data of one data acquisition flight only so that the physical state can be considered as being static. Thus the time scale τ can be chosen as fast as allowed by the computer the dynamics is iterated on.

A. The Sensor Contribution

In (1) the term $F_i^{(S)}$ is the contribution from the sensors. As we already mentioned, the three radiometers of our example provide raw intensity measurements of the electromagnetic radiation within the corresponding frequency domain only. The physical model [4] transforming these measured intensities (T_1, T_2, T_3) into sensor estimates of the oil film thickness is complicated and still under development. The main aspect of this model is, however, that interference effects between the backscattering from the oil-water- and oil-air-surface lead to an ambiguity of the transformation: for a given intensity measurement T_n a number of different thickness values $D_{n,m}$ are possible which differ in multipliers of the corresponding sensor's wavelength. For our sensor fusion system we therefore assume that each sensor n "votes" for a number of M different thickness values $D_{n,m}$ and we require that the sensor fusion mechanism must disambiguate the information autonomously. The contribution $F_i^{(S)}$ has the form:

$$F_i^{(S)} = \sum_{n=1}^{N} \sum_{m=1}^{M} f_{i,n,m} \qquad (2)$$

$$f_{i,n,m} = \gamma_n(\vec{r}_i)(D_{n,m}(\vec{r}_i) - d(\vec{r}_i)) e^{-\frac{(D_{n,m}(\vec{r}_i)-d(\vec{r}_i))^2}{2\sigma_S^2}}$$

Every sensor measurement $D_{n,m}(\vec{r}_i)$ specifies a local attractor at $d(\vec{r}_i) = D_{n,m}(\vec{r}_i)$ for the dynamic state variable $d(\vec{r}_i)$ as $f_{i,n,m}(d(\vec{r}_i) = D_{n,m}(\vec{r}_i)) = 0$ and $\frac{\partial f_{i,n,m}}{\partial d(\vec{r}_i)}|_{d(\vec{r}_i)=D_{n,m}(\vec{r}_i)} < 0$. These local attractors have different strengths $\gamma_n(\vec{r}_i)$ depending on the reliability of the corresponding sensor n. The γ_n are system parameters which can either be chosen constant according to a general knowledge about the sensors' reliabilities or they can be gained analysing the resulting global equilibrium state of the dynamics as we will describe later. The attractors are equipped with a *basin of attraction* of constant width σ_S. The effect of this range can be understood regarding Fig.1: Local attractors $f_{i,n,m}$ with overlapping basin of attraction result in a broad global attractor at an intermediate average position when they are summed up in (2). Isolated local attractors, however, remain isolated in the sum $F_i^{(S)}$ (see Fig.1, D_{11}). The more local attractors overlap, the broader and stronger the intermediate attractor becomes. As the local attractors represent information about the physical quantity to estimate, this principle is an effective way to control the reliability of the final estimate.

B. Neighbourhood Contribution and A Priori Knowledge

The principle of representing information as localized attractors can be exploited by taking into account additional

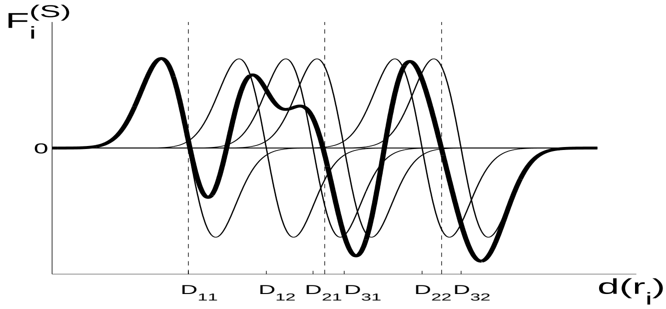

Fig. 1. The sensor contribution $F_i^{(S)}$ from (2) for the example of three sensors each of which specifies two possible measurements ($N = 3, M = 2$). The sum $F_i^{(S)}$ (thick solid line) of the local attractors (thin solid lines) specifies three attractors (indicated by the dashed verticals) for the sensor contribution $F_i^{(S)}$ of the thickness estimate. Overlapping local attractors (here: (D_{12}, D_{21}, D_{31}) and (D_{22}, D_{32})) specify intermediate attractors.

knowledge about the physical system to measure. We will give two examples.

From the hydrodynamic characteristics of the oil film it is known that the thicknesses $\tilde{d}(\vec{r}_i)$ and $\tilde{d}(\vec{r}_j)$ of nearby locations ($|\vec{r}_j - \vec{r}_i| < \epsilon$) does not differ very much. Therefore we can use the estimates $d(\vec{r}_j)$ in the ϵ-neighbourhood of a location $\vec{r}_i$ as additional cues for the estimate $d(\vec{r}_i)$:

$$F_i^{(\epsilon)} = \sum_j g(|\vec{r}_j - \vec{r}_i|)(d(\vec{r}_j) - d(\vec{r}_i)) e^{-\frac{(d(\vec{r}_j)-d(\vec{r}_i))^2}{2\sigma_\epsilon^2}}$$
$$\forall j \quad \text{with} \quad |\vec{r}_j - \vec{r}_i| < \epsilon \qquad (3)$$

In (3) local attractors specified by the neighbouring estimates are summed up weighted by a Gaussian function $g \propto \exp(-\frac{(|\vec{r}_j - \vec{r}_i|)^2}{2\epsilon^2})$. The basin of attraction σ_ϵ of the local attractors is chosen larger than σ_S, the one of the sensor contribution. However, the relative strength λ_ϵ of the neighbourhood contribution in (1) is chosen smaller than λ_S, the one of the sensor contribution. This implements the feature of *outlier elimination*: if one or more local sensor measurements $D_{n,m}$ differ from the estimates of the neighbouring locations, the broad neighbourhood attractors together can vote down even strong local sensor-attractors. This way the system can autonomously correct for a number of errors, such as spikes, temporal breakdowns or short-time decalibrations of the sensors. It is important to mention that the nonlinearity of the system imposed by the limited range of the attractors is a crucial characteristic of the method: outliers, voting for a value of the dynamic state variable which differs very much from the average, are discarded as their basin of attraction does not overlap with the rest of the attractors.

Depending on the availability, even a priori or expert knowledge can be used to help the system to quickly converge into a globally stable state. It is known, for instance, that an oil film diffuses in such a way that the thickness is maximal at the origin of the pollution. Therefore, a contribution $F_i^{(A)}$ can be formulated, which slightly favors larger values $d(\vec{r}_i)$ in the center of the contaminated area and smaller values at its border.

C. Setting the Initial State and the Parameters

All attractor contributions are summed up in (1) to a coupled nonlinear dynamical system. Whether or not this system converges to a global stable state depends very much on the initial state $d(\vec{r}_i)|_{t=0}$ of the dynamics. A good choice is the linear average of the sensor inputs:

$$d(\vec{r}_i)|_{t=0} = \frac{1}{NM} \sum_{n=1}^{N} \sum_{m=1}^{M} D_{n,m}(\vec{r}_i) \quad (4)$$

In simulations we found out, that the system parameters σ, ϵ and γ are less crucial for the overall performance of the mechanism and can be selected from a relatively wide range of possible values. However, the basins of attraction for the local attractors must be sufficiently large to avoid that the global estimate gets stuck in a suboptimal state.

The relative strengths γ_n in (2) represent the reliability of the corresponding sensors. If this information is not available a priori, an estimate for the sensors' reliabilities can be gained a posteriori by comparing the sensor estimates $D_{n,m}(\vec{r}_i)$ with the stable state $d(\vec{r}_i)|_{t\to\infty}$ the system converges to: A sensor which deviates from the stable state at many locations $\vec{r}_i$ is less reliable and its relative strength γ_n is reduced proportional to this deviation. Further sensor fusion processes with the same system profit from this information by an accelerated convergence as the unreliable sensors have less influence on the overall estimate.

IV. Results

We tested our approach in a number of simulations. Fig.2 shows an example in which three fictive sensors provide measurements of a simulated thickness distribution. The sensor signals were perturbed by stochastic and systematic noise from 3 to 20% of the amplitude. In addition correlated and uncorrelated spikes were added to the sensor signals. The right lower panel in Fig.2 shows that unlike a conventional smoothing filter, for instance, our sensor fusion dynamics eliminates the perturbations without changing the shape of the original distribution. The dynamics extracts the original information contained in the noisy data. Fig.3 shows real data from an experiment in which a ship deposed a small amount of oil the radiation of which was measured by three radiometers during a flight acrosss the contaminated area. The fusion dynamics eliminates the sensor noise by exploiting the fact that the major part of this noise is not correlated between the three sensors.

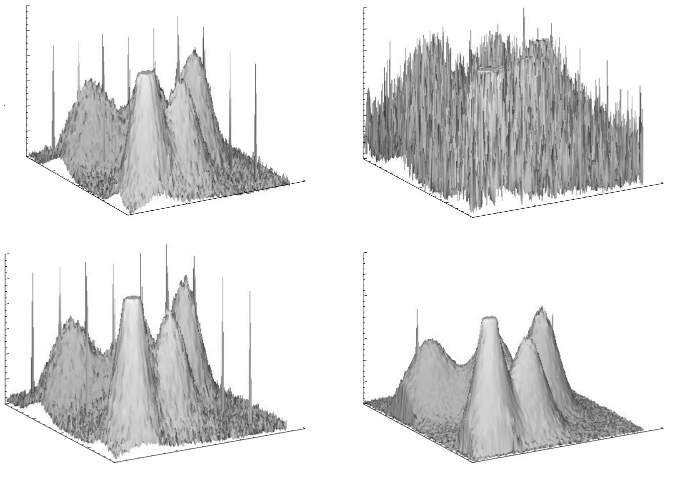

Fig. 2. The right lower panel shows the stable state of the sensor fusion dynamics resulting from three simulated sensor inputs displayed in the other panels. The axis units are arbitrary for this sample simualtion.

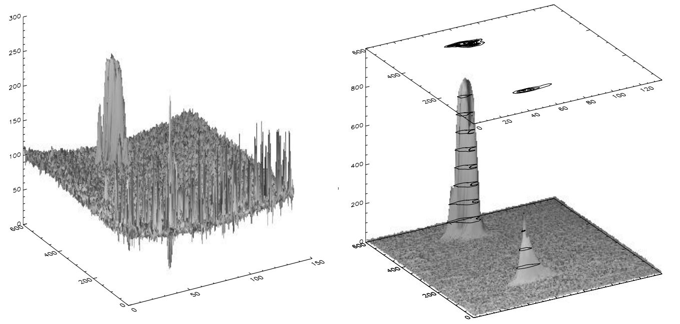

Fig. 3. The left panel shows the linear average of the three sensor outputs provided by three radiometers in a real experiment. Note the high noise level in the foreground. The right panel shows the stable state to which the sensor fusion dynamics has converged after 5 iterations. The peak in the foreground stems from the radiation emitted by the ship which has deposed the oil before.

V. Discussion

We demonstrated the power of the dynamic approach to sensor fusion in simulation and experiment. The mechanism is particularly suited for high levels of sensor noise, partly corrupted data and situations in which no calibration measurements are available. Unlike with neural nets, no training data is needed to configure the sensor fusion system. In contrast to linear methods like Least Squares Estimators or simple averaging [6], our system is entirely nonlinear allowing for automatic outlier elimination. Unlike rule based mechanisms like Fuzzy Logic systems for instance, our approach expresses all sorts of information by one simple concept only: the local attractor. Therefore, the sensor fusion dynamics can be extended easily to incorporate additional sources of information. Due to the fact that only a simple *EULER* iteration of the differential equations is required to solve the dynamics, the method is fast and can be easily parallelized.

References

[1] P.K. Varshney, ed. . "Special Issue on Data Fusion". Proceedings of the IEEE, vol. 85, no. 1, Jan 1997.

[2] R.R. Brooks and S.S. Iyengar. "Multi–Sensor Fusion". Prentice Hall, 1998.

[3] German Ministry of Transportation (BMV). "Luftüberwachungssystem zur Erkennung von Meeresverschmutzungen". Information Brochure, 1998.

[4] F.T. Ulaby, R.K. Moore, and A.K. Fung. "Microwave Remote Sensing", Vol. I–III. Addison–Wesley, 1981.

[5] A. Steinhage and G. Schöner. "Dynamical Systems for the Behavioral Organization of Autonomous Robot Navigation". in Sensor Fusion and Decentralized Control in Robotic Systems: Proc. of SPIE, P.S. Schenker and G.T. McKee, Eds., SPIE-publishing, 1998, pp 160-180.

[6] C.M. Bishop. "Neural Networks for Pattern Recognition". Oxford University Press, 1995.