Data Fusion for Modern Engineering Applications: An Overview

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Abstract. An overview of data fusion approaches is provided from the signal processing viewpoint. The general concept of data fusion is introduced, together with the related architectures, algorithms and performance aspects. Benefits of such an approach are highlighted and potential applications are identified. Case studies illustrate the merits of applying data fusion concepts in real world applications.

1 Introduction

The data fusion approach combines data from multiple sensors (and associated databases if appropriate) to achieve improved accuracies and more specific inferences that could not be achieved by the use of only a single sensor [1]. This concept is hardly new:- living organisms have the capability to use multiple senses to learn about the environment. The brain then **fuses** all this available information to perform a decision task.

One of the first definitions of data fusion came form the North American Joint Directors of Laboratories (JDL) [2,3], who define data fusion as a:- *multilevel, multifaceted process dealing with the automatic detection, association, correlation, estimation and combination of data from single and multiple sources.*

Data fusion principles apply to many domains, and have been (often implicitly) at the core of modern applications in the diverse areas spanning engineering, computing, and biomedicine. The recent interest in the theory and taxonomy of multisensor data fusion has been reflected by a number of special issues of leading international journals and conferences, which have been dedicated to this

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area (e.g. Proc. of the IEEE in 1997 [1] and 2003 [4], JMLR in 2003 [5], and IEEE TNN 2002 [6]).

There has been a somewhat conflicting use of terminology within the data–sensor–information fusion community. People working at the sensor level view data fusion as basically operating with raw data which have undergone at the most only some preliminary processing [7]. Others, like JDL, have a more general view which includes both raw and processed data – in short, all the inputs to some higher level decision making/classifying stages.

Our aim in this paper is therefore to provide a systematic overview of the existing data fusion philosophy and methods for engineering applications.

2 Data Fusion Principles

When approaching a problem from the data fusion viewpoint, we differentiate between the following levels of abstraction:

- **Observation/measurement space** contains vectors of measurement functions which can be univariate, multivariate, and/or multidimensional, depending on temporal, spatial or other independent variables. It may be possible to build a state–space model, or to assess the data modality [8,9];
- **Transform domain representations**, which seek features from time and/or frequency models (fast Fourier transform (FFT), (nonlinear) autoregressive (N)ARMA models [10], wavelet), blind processing (independent component analysis (ICA), blind source separation (BSS) [11]), particle/Kalman filter [12], kernels and support vector machines (SVM) [25], kernel ICA);
- **Decision space**, where the classes within the data fusion model (and the corresponding basins of attraction from the measurement space) are mapped into the relevant probabilities of the occurrence of an event.

Similarly, authors distinguish between the Data, Information, and Knowledge semantic levels [14] (Figure 1). This simple taxonomy has been very useful in the diverse applications of data fusion, such as in:- i) *transportation*, aviation, intelligent car traffic and motorways management; ii) *multimedia communications*, audio–visual fusion for teleconferencing; iii) *robotics*, 3-D vision; iv) *wearable computing*, monitoring the disabled and elderly.

2.1 Models of Data Fusion

Data fusion is based on the manipulation of multiple measurements, where *classifiers* operate on *features* extracted from the real world *measurements*; an overview

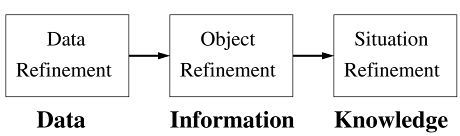

Fig. 1. General data fusion concept

of the ways for combining classifiers can be found in [15]. Authors distinguish between the two fusion classes:-

i) **Data fusion**, where the classifier operates on either the *raw data* or *features* extracted directly from the measurements;
ii) **Decision fusion**, where the decisions from the *individual classifiers* for different data channels are *combined.*

The choice depends on the statistical relationship between the data channels, mutual entropy, or joint Gaussianity [16], and to this end coupling of mathematical modelling and information processing is under investigation [17]. The main issues are signal nonlinearity (with associated non–Gaussianity), nonstationary, intermittent data natures and noises. This makes it very difficult to perform estimation by standard methods since no assumption on the data model and distribution can be ascertained. In some applications, such as functional Magnetic Resonance Imaging (fMRI), there is even no "ground truth", to rely upon. Multisensor practical systems therefore aim at providing higher accuracy and improved robustness against uncertainty and sensor malfunction [18], and also for the information extracted from different sources to be integrated into a single signal or quantity.

Signal processing algorithms for "sensor" or "data fusion" can be based on [19]:-

– *Probabilistic models:* Bayesian reasoning, evidence theory, robust statistics;
– *Least squares:* Kalman filtering, regularization, set membership;
– *Intelligent fusion:* Fuzzy logic, neural networks, genetic algorithms.

One of the first proposed data fusion models was the "waterfall model" (Figure 2), developed for the UK Defence Evaluation Research Agency (DERA) [3].

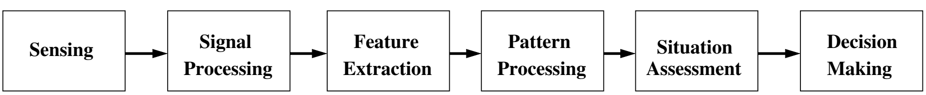

Fig. 2. The Waterfall model

2.2 Data Fusion and Sufficient Information

We can think of the heterogeneous sensors monitoring a certain process as being "windows" into the phenomenon under observation. Sensors can either have their own window, or the windows "overlap" in space or time. This way, the information obtained can be thought of as "decomposed" or "fragmented" by the sensors, which is sometimes called sensor fission [7], and is related to so–called *sufficient information* (whether the character and number of sensors can indeed describe the phenomenon). This is analogous to the notion of *embedology*, where we wish to model the nonlinear dynamics of a multidimensional process based on its time delay representation [8]. The information fragments coming from sensors are exposed to spectral shaping, saturation, and noise; *data fusion* aims at retrieving the "interesting" characteristics of the phenomenon.

3 Architectures and Performance Aspects

Combining multi–sensor data in the data fusion framework has the potential of faster and cheaper processing and new interfaces, together with reducing overall uncertainty (increase in reliability). Such data can be combined in various ways, for instance by:- i) linear combiner, ii) combination of posteriors (weights, model significance), iii) product of posteriors (independent information). Based on the different ways of combining information and different semantic levels, we differentiate between the following data fusion architectures, shown in Figure 3:-

– **Centralised:** simple algorithms, but inflexible to sensor changes;
– **Hierarchical:** collaborative processing, two way communication;
– **Decentralised:** robust to sensor changes and failures, complex algorithms.

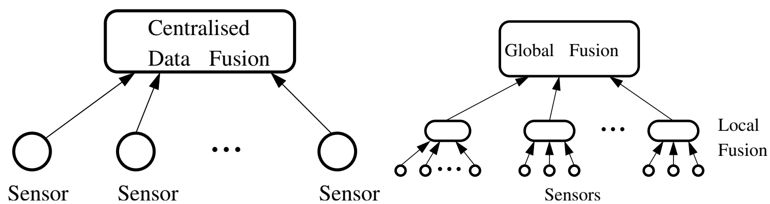

Fig. 3. Centralised and hierarchical data fusion

This synergy [20] of information fragments offers some advantages over standard algorithms, such as:-

– Improved confidence due to complementary and redundant information;
– Robustness and reliability in adverse conditions (smoke, noise, occlusion);
– Increased coverage in space and time; dimensionality of the data space;
– Better discrimination between hypotheses due to more complete information;
– System being operational even if one or several sensors are malfunctioning;
– Possible solution to the vast amount available information.

The paradigm of *optimal fusion* in this sense is to *minimise* the probability of unacceptable error.

Based on the taxonomy presented in Section 2, depending on the stage at which fusion takes place, data fusion is often categorized as the *low*– (LLF), *intermediate*– (ILF) or *high*–level (HLF) fusion, where:-

– LLF (*data fusion*) combines raw data sources to provide better information;
– ILF (*feature fusion*) combines features that come from heterogeneous or homogeneous raw data. The aim is to find *relevant* features amongst various features coming from different methods (FFT, discrete cosine transform (DCT), wavelet, delay vector variance (DVV) [9]);
– HLF (*decision fusion*), combines decisions or confidence levels coming from several experts (*hard* and *soft* fusion).

In practice, any combination of these three levels can be employed, for instance [7]: *Data in – Data out, Data in – Feature out, Feature in – Feature out, Feature in – Decision out, Decision in - Decision out.*

4 Data Alignment and Fusion of Attributes

Depending on where the fusion process occurs, open literature differentiates between the *temporal*, *spatial*, and *transform domain* fusion. Notice, however, that the latter two can be considered as examples of the low– or intermediate–level fusion. Temporal fusion is different in the sense that it may occur at any level:- inputs from one sensor taken at different instants are combined.

The information entering a fusion process should be aligned, a difficult problem for which there is no general supporting theory. Alignment should be applied to both homogeneous (commensurate) and heterogeneous (non–commensurate) information, which may require conversion or transformation of observations [13].

The concept of alignment assumes "common language" between the inputs, for instance:- i) standardisation of measurement units; ii) sensor calibration; or iii) corrections for different illuminants and shading [21]. Alignment may operate at any of the three semantic levels: *measurements*, *attributes*, and *rules*, with possible crossings between levels [21]. For instance, for aligned and associated sources of information, fusion of attributes concatenates attributes of the same object, derived from different representations of the object. Fusion of representations performs meta–operations, it is applicable to any representation, and can be combined with other types of fusion.

Data fusion also applies to cyberspace, where intrusion detection (ID) systems fuse data from heterogeneous distributed network sensors to create "situational awareness" [14], such as the detection of network anomalies and virus attack. Information of interest are the identity, threat, rate of attack, and target of intruders [22].

Performance aspects of a fusion system [20] are domain–specific:-

- Detection performance and characteristics (false alarm rate);
- Spatial/temporal resolution and ability to distinguish between signals;
- Spatial and temporal coverage (span or viewfield of a sensor);
- Detection/tracking mode (scanning, tracking, multiple target tracking);
- Measurement accuracy and dimensionality.

5 Case Studies

We next provide three case studies to illustrate the data fusion concept:- the examples in car navigation, sleep science and multimedia.

Car navigation systems perform three main tasks: positioning, routing and navigation (guidance). The car position is calculated from several information sources including on–board odometers and gyroscopes, the global positioning system (GPS) and digital maps. On–board sensors measure acceleration and

angular rates, for which the short–term precision is high, but the accumulated errors grow with time, producing a poor long–term position estimate.
On the other hand, the GPS exhibits excellent overall performance, but its accuracy is highly sensitive to factors such as "blind" areas (tunnels, garages) and the number of "visible" satellites. One way to circumvent these sensor limitations would be to exploit the potential a combination of the short–term accuracy of on–board sensors and long–term accuracy of the GPS system.
This has been achieved in the Siemens car navigation system [23], where the *fusion* of the information from vehicles' internal sensors and the GPS position reading provides 80% improved navigation accuracy within the given time interval as compared to the estimate based on the on–board sensors only.

Awareness/fatigue modelling is important in the detection of sleep stages and also for the detection of microsleep for drowsy drivers. The observed signals are the electroencephalogram (EEG), electro-oculogram (EOG), and respiratory signal. There are also several sources of artifacts, such as the eye blink artifact in EEG. Although it is possible to detect sleep stages or microsleep events using only one sensor modality (typically EEG), the classification accuracy is not sufficient to warant real world applications, and the data fusion approach is one viable solutions which combines the EEG and EOG features. In addition, in order to achieve high detection and classification rates, the temporal fusion over the observation windows is even more important than feature selection. For sleep stage detection, feature fusion can be performed using the DVV method [9], which gives features related to the signal nonlinearity [24]. Such a fusion of EEG and EOG features provides $\approx$ 99% accuracy in training and $\approx$ 90 % accuracy on test data. Similarly, the feature fusion of EEG and EOG channels significantly improves the detection of microsleep [26].

Video assisted speech separation, where the task is to integrate complementary audio and visual modalities to enhance speech separation. Rather than using independence criteria suggested in most BSS systems, visual features from a video signal are used as additional information to optimise separation. The Bayesian framework can be applied for feature fusion, where the mel–frequency cepstrum and "active apperance model" provide audio and video features. This way a performance improvement of several dB can be achieved [27].

6 Conclusions

Data fusion provides a theoretical, computational, and implementational framework for combining data and knowledge from different sources with the aim of maximising the useful information content. In this way, reliability and discrimination capability are improved while the amount of required data is minimised. Through the three overlapping stages: preprocessing, data alignment, and decision making, the performance of a system is improved. Data fusion spans disciplines such as signal detection, pattern recognition, and tracking, with applications in domains such as military, robotics, medicine, and space research. This paper sumarises some of the recent developments in data fusion, and gives an overview of concepts, architectures and potential benefits of using this approach.

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