Institut für industrielle Informationstechnik
Institute Industrial IT

Information Fusion – Introduction

Combination Techniques for Uncertain Information in Measurement and Signal Processing

inIT steht für Zukunft.
Im Technologie-Netzwerk: Intelligente Technische Systeme OstWestfalenLippe
it's owl

Information Fusion Prof. Dr.-Ing. Volker Lohweg

Institut für industrielle Informationstechnik
Institute Industrial IT

Lectures – Contents

Information Fusion Only valid with verbal explanations Prof. Dr.-Ing. Volker Lohweg 2

Institut für industrielle Informationstechnik
Institute Industrial IT

1.1 Why Information Fusion?

Definition 1.1: Information

Information is data in context. It can be the description of a mapping towards human or technical *knowledge.*

Definition 1.2: Signal

A signal is the *carrier* of data (information) and can be interpreted as a physical description of information. A signal can be one-dimensional or more-dimensional.

Information Fusion Only valid with verbal explanations Prof. Dr.-Ing. Volker Lohweg 3

Institut für industrielle Informationstechnik
Institute Industrial IT

1.1 Why Information Fusion?

Definition 1.3: Sensor Fusion

Sensor Fusion is information fusion from multiple sensors of different or the same type.

Definition 1.4: Information Fusion *

Information Fusion is combined information of data to estimate or predict the state of some *real world situations.*

*) verbal comment on the wording Data Fusion

Information Fusion Only valid with verbal explanations Prof. Dr.-Ing. Volker Lohweg 4

Institut für industrielle Informationstechnik
Institute Industrial IT

1.1 Why Information Fusion?

MISSION:

Study the benefits of using simultaneous information from multiple sensors to probe the environment.

EXAMPLES

- Industrial Information Fusion in **Intelligent Automation** (Hot Topic in Industrie 4.0 / Research topic in inIT)
- Robotics
- Infrared / Millimeter wave radar for vehicle detection and identification
- Chemical sensor arrays – "artificial nose"
- Biomimetics – imitating animal sensorimotor behaviors

Information Fusion Only valid with verbal explanations Prof. Dr.-Ing. Volker Lohweg 5

Institut für industrielle Informationstechnik
Institute Industrial IT

1.1 Why Information Fusion?

Research Topic in Leading Edge Cluster it's OWL – Intelligent Technical Systems

Information Fusion Only valid with verbal explanations Prof. Dr.-Ing. Volker Lohweg 6

Institut für industrielle Informationstechnik
Institute Industrial IT

1.1 Why Information Fusion?

Institut für industrielle Informationstechnik
Institute Industrial IT

1.1 Why Information Fusion?

Learn sensor fusion from animals. Apply this to flying a drone to target using onboard video.

Flies land accurately

Bees find flowers

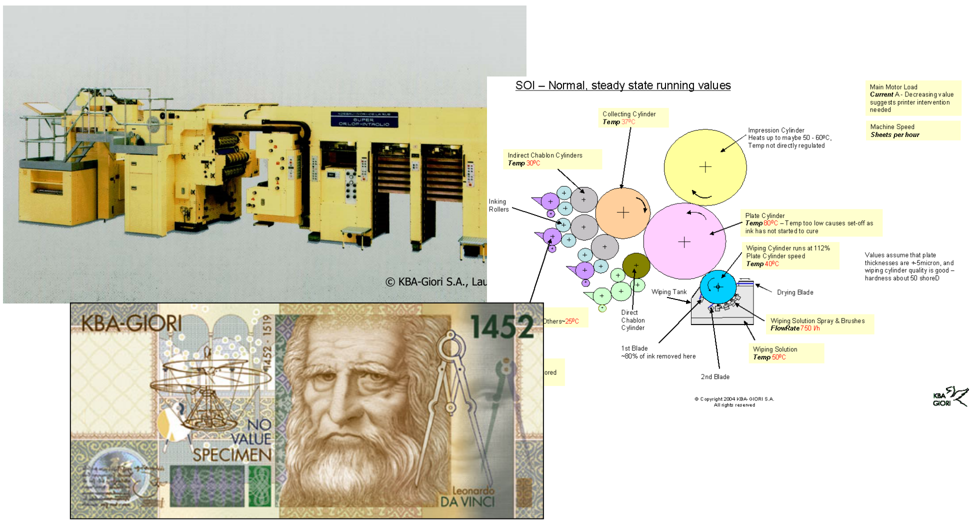
Bats catch evading insects in flight

inIT Institut für industrielle Informationstechnik
Institute Industrial IT

1.1 Why Information Fusion?

inIT Institut für industrielle Informationstechnik
Institute Industrial IT

1.1 Why Information Fusion?



Institut für industrielle Informationstechnik
Institute Industrial IT

1.1 Why Information Fusion?

~~Defence Applications~~

Defence and Military Applications will not be highlighted.

Information Fusion Only valid with verbal explanations Prof. Dr.-Ing. Volker Lohweg 11

Institut für industrielle Informationstechnik
Institute Industrial IT

1.2 Information and Measurement

- From where do we get the information? → Sensors
- Optical
  - Photodetectors
  - Cameras: B/W, Colour, Infrared (IR), Ultraviolet (UV)
- Pressure
- Distance
- Angle
- Position, etc.
- Problems:
  - **Random errors**
    - e.g. noise (different sources), further stochastic effects, etc.
  - **Systematic errors**
    - e.g. alignment errors

Information Fusion Only valid with verbal explanations Prof. Dr.-Ing. Volker Lohweg 12

Institut für industrielle Informationstechnik
Institute Industrial IT

1.2 Information and Measurement

- Measurement results provide data.
  - **They are information, iff the data is in context**
  - **They might contain knowledge (How to get knowledge?)**
- Questions
  - Does the measurement process provide *complete knowledge* about the measurand (the object which is measured)?
  - Is the quality of the measurement good enough for a real world application?
  - How do we tackle the problem of *incomplete knowledge*?

Institut für industrielle Informationstechnik
Institute Industrial IT

1.2 Information and Measurement

- Example 1.2-1
  - Two technicians use a measurement device (MD) for width measurement of tyres. The MD has to be adjusted manually with a setting jig (gauge).
    - Technican 1 measures 240 mm.
    - Technican 2 measures 242 mm.
  - Questions
    - Is one of them wrong?
    - Are they both wrong?
    - Or perhaps are they both right? (is this strange?)

Institut für industrielle Informationstechnik
Institute Industrial IT

1.2 Information and Measurement

- Example 1.2-1, cont'd
  - It is quite likely that different effects will affect the measurement, including
    - Justage / Human factor
    - Employed instrumentation
    - Measurement temperature, etc.
  - Obviously the tyre width can not be both 240 mm and 242 mm, it must be concluded that the effect of these *influence quantities* has caused the difference between the measured values and the actual width of the tyre.

Institut für industrielle Informationstechnik
Institute Industrial IT

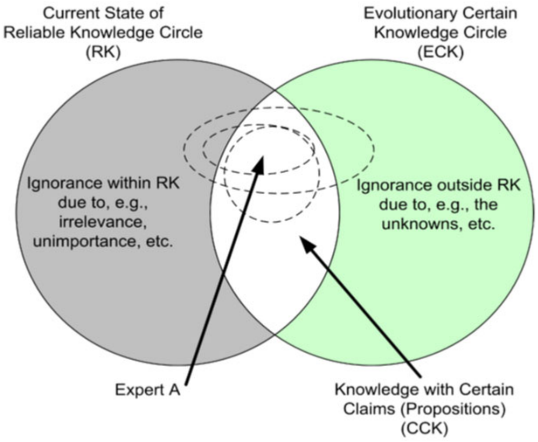
1.2 Information and Measurement – Taxonomy of Uncertainty

- Creating reliable knowledge about a machine process is a challenge because it is a known fact that **Data** $\neq$ **Information** $\neq$ **Knowledge**.
- Insofar, a fusion process must create a low amount of data which creates reliable knowledge.
- Usually the main problems in information fusion is described as follows:

  Too much data, poor models, bad features or too many features, and improperly analysed applications.
- One major misbelief is that machine diagnosis can be handled only based on the generated data—knowledge about the technical, physical, chemical, or other processes are indispensable for modelling a multi-sensor system.

1.2 Information and Measurement – Taxonomy of Uncertainty

- Human evolutionary and trained knowledge.



1.2 Information and Measurement – Taxonomy of Uncertainty

- Usually two types of ignorance can be identified:
  - **blind ignorance** with its subcategories
    - unknowable,
    - irrelevance, and
    - fallacy* (camouflage**);
  - **conscious ignorance** with its subcategories
    - inconsistency (confusion, conflict, inaccuracy) and
    - incompleteness (absence, unknowns, uncertainty).

DE: *Irrtum; **Tarnung

Institut für industrielle Informationstechnik
Institute Industrial IT

1.2 Information and Measurement – Taxonomy of Uncertainty

- **Aleatoric uncertainty**

  If data is complete and intrinsically nondeterministic in nature, it can be assumed as random (stochastic). The uncertainty is attributed to real-world phenomena and it can not be reduced or even eliminated by expanding an underlying knowledge base. Probabilistic approaches, such as classical Probability Theory (frequentist) and Bayesian Probability Theory are an effective way to model stochastic uncertainties, like measurement noise, etc. This type of uncertainty is referred to as aleatoric uncertainty (cf. Table 1).

Institut für industrielle Informationstechnik
Institute Industrial IT

1.2 Information and Measurement – Taxonomy of Uncertainty

- **Epistemic uncertainty**

  In many situations we lack information, that is, not all intrinsically necessary knowledge is available at state. In this case, the uncertainty range should be reduced by expanding the underlying knowledge base. When data is scarce the probabilistic approach may not be appropriate to reduce the system's uncertainty. Major types of this uncertainty are inconsistent and incomplete data, information or knowledge. **In many cases this uncertainty can be reduced by multi-sensory fusion and expert's knowledge.** This type of uncertainty is referred to as epistemic uncertainty (cf. table 1).

inIT Institut für industrielle Informationstechnik
Institute Industrial IT

1.2 Information and Measurement – Taxonomy of Uncertainty

- Classification of aleatoric and epistemic uncertainty

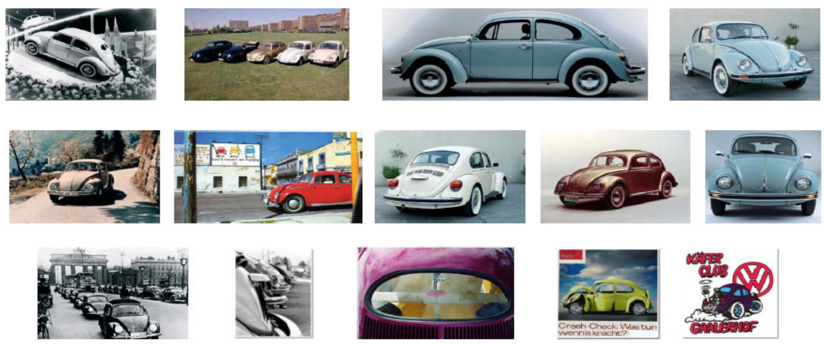
	Aleatoric Uncertainty	*Epistemic Uncertainty*
Type	irreducible	reducible
Data	random, stochastic	scarce
Origin	intrinsic variations in data	inconsistent & incomplete data, lack of knowledge
Model	Probability Theory	Evidence and Fuzzy Theories

Lohweg, Volker; Voth, Karl; Glock, Stefan: A Possibilistic Framework for Sensor Fusion with Monitoring of Sensor Reliability, Sensor Fusion – Foundation and Applications. Intech Publishers, Vienna, July 2011, Jul 2011.

inIT Institut für industrielle Informationstechnik
Institute Industrial IT

1.3 Information and Pattern Recognition

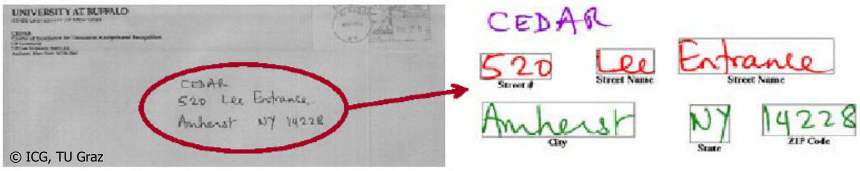
- Example 1.3-1
  - Class "VW-Beetle", AI: Artificial Intelligence



Institut für industrielle Informationstechnik
Institute Industrial IT

1.3 Information and Pattern Recognition

- Example 1.3-2: Pattern assignment
  - Class "Character Recognition", Work topic: Numerical Classification.



Information Fusion Only valid with verbal explanations Prof. Dr.-Ing. Volker Lohweg 54

Institut für industrielle Informationstechnik
Institute Industrial IT

1.3 Information and Pattern Recognition

- Detection power Humans vs. Machine (Computer, etc.)

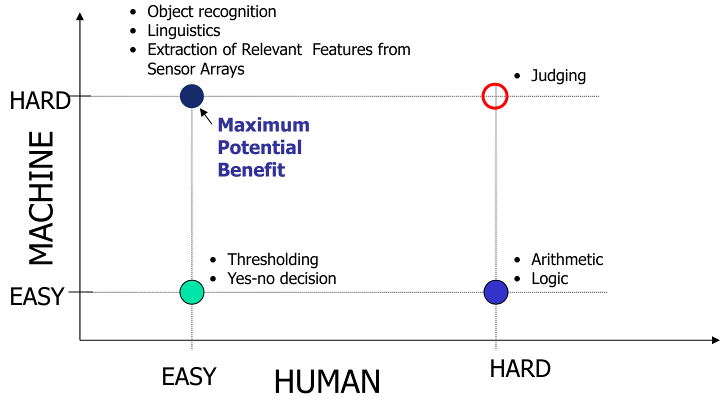
	Human	Technical System
Associative Ability	☺	☹
Combinatorial Ability	☹	☺

Information Fusion Only valid with verbal explanations Prof. Dr.-Ing. Volker Lohweg 55

Institut für industrielle Informationstechnik
Institute Industrial IT

1.3 Information and Pattern Recognition

- Problem Complexity: Humans vs. Machine



Information Fusion Only valid with verbal explanations Prof. Dr.-Ing. Volker Lohweg 56

Institut für industrielle Informationstechnik
Institute Industrial IT

1.3 Information and Pattern Recognition

- Patterns
  - Patterns are objects, which have pre-defined descriptive information signature.
  - One-dimensional patterns are defined by vectors (discrete signals). Two-dimensional patterns are defined by matrices (e.g. digital images).

Information Fusion Only valid with verbal explanations Prof. Dr.-Ing. Volker Lohweg 57

Institut für industrielle Informationstechnik
Institute Industrial IT

1.3 Information and Pattern Recognition

- Classes
  - Patterns are mapped into different classes, independetely regarding their apperance. Two discrete signals (pattern) are *equivalent*, if they are allocated by a pattern recognition system to one specific class. All equivalent patterns are allocated to one so called *equivalent class* (in short: *class*).
    - WOLKEN: Cumulus, Cirrus, Stratus, ...



    - BLÄTTER: Eiche, Buche, Ahorn, Walnuß, ...

  - Zusammenfassung vieler verschiedener Objekte unter gemeinsamen Eigenschaften, ausgewählt aus der Menge der Eigenschaften, die ein Objekt beschreiben.

Information Fusion Only valid with verbal explanations Prof. Dr.-Ing. Volker Lohweg 58

Institut für industrielle Informationstechnik
Institute Industrial IT

1.3 Information and Pattern Recognition

- Classification
  - Classification defines the assignment (or allocation) of objects in groups which belong to one class. The classification criteria are heavily dependent on the application.
  - Examples: speech recognition (speaker dependent, speaker independent, content dependent, content independent, etc.)
  - Automatic pattern recognition: Systems which have the ability to allocate new objects (patterns) to known classes (not simple!)

Information Fusion Only valid with verbal explanations Prof. Dr.-Ing. Volker Lohweg 59

Institut für industrielle Informationstechnik
Institute Industrial IT

1.3 Information and Pattern Recognition

- Class allocation
  - Semantical classes
    - Semantical classes conclude all objects (technical or human-centric information) which are content-orientated similar or identical. Their generation is usually human expert based. The class allocation is know-how or standpoint based.
  - Natural classes
    - Natural classes are formed by information which is equivalent in a formal sense. They are based on mathematical formalisms which are based on distances between objects or different object clusters. Natural classes are the base for the numerical classification.

Institut für industrielle Informationstechnik
Institute Industrial IT

1.3 Information and Pattern Recognition

- Features
  - A feature *m*, or a feature vector ***m*** is generated from sensory information.
  - Features are the base of pattern recognition. They define different pattern signatures which are detectable and allocatable. Whether they are able to distinguish between all equivalent classes can not be deducted.

Institut für industrielle Informationstechnik
Institute Industrial IT

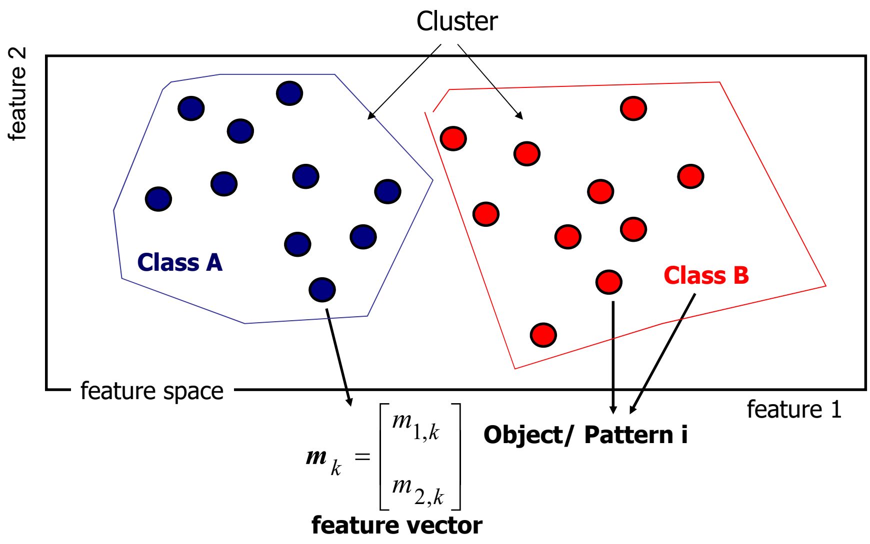
1.3 Information and Pattern Recognition

- Feature space, Cluster
  - Feature space
    - A feature space is a P-dimensional space M which is defined (span of a vector space) by P features ***m.***
    - Is a class C "properly" represented by a number of P features, then all feature vectors should be located in a narrow area in the feature space.
  - Cluster
    - Is a class C located in a narrow area in the feature space (the *intra-class distance is low)*, it is said to be a *Cluster.*
    - Patterns can be separated into different classes, if the pattern clusters have a *large inter-class distance* between each other.
    - Do the clusters partly overlap it is not possible to separate distinct classes. Usually the features are not chosen optimally (real world situation!).

Information Fusion | Only valid with verbal explanations | Prof. Dr.-Ing. Volker Lohweg | 62

Institut für industrielle Informationstechnik
Institute Industrial IT

1.3 Information and Pattern Recognition



Information Fusion | Only valid with verbal explanations | Prof. Dr.-Ing. Volker Lohweg | 63