# Characterization of hard and soft sources of information: A practical illustration

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***Abstract*—Physical sensors (hard sources) and humans (soft sources) have complementary features in terms of perception, reasoning, memory. It is thus natural to combine their associated information for a wider coverage of the diversity of the available information and thus provide an enhanced situation awareness for the decision maker. While the fusion domain mainly considers (although not only) the processing and combination of information from hard sources, conciliating these two broad areas is gaining more and more interest in the domain of hard and soft fusion. In order to better understand the diversity and specificity of sources of information, we propose a functional model of a source of information, and a structured list of dimensions along which a source of information can be qualified. We illustrate some properties on a real data gathered from an experiment of light detection in a fog chamber involving both automatic and human detectors.**

**Keywords: Hard and soft fusion; Sources; Quality; URREF; Detection.**

## I. Introduction

According to Wikipedia, an *information source* is "anything that might inform a person about something or provide knowledge about it". The notion of source is not understood the same way within different communities: Physicists in optics talk of a light source as a source of information; physical sensors (ESM, cameras, AIS, etc) are commonly referred to as sources of information within the tracking community; in the intelligence domain, sources are witnesses/observers, as well as the generated observation reports, etc; in other fields, databases are also sources of information; etc. It seems challenging to come up with a unified characterization of objects of such different natures. The characterization of information quality has been widely addressed in the literature (*e.g.* [1], [2], [3]) in defining Information Quality Dimensions (IQD). Information quality strongly relies on *source quality* which received less attention. Because the primary reason of existence for a source is to provide information, a source should be assessed primarily according to the information it outputs. However, source quality (SQ) differs from information quality (IQ): SQ is more or less perennial, the quality of a source being assessed on its ability to provide information based on past experiences, while IQ is instantaneous. In [4], the source of information and the information produced by the sources are assessed independently: A "good" source can provide "bad" information at a given time. The dimensions are unique for each of these elements, *reliability* for the source quality and *credibility* for the information quality.

The proliferation of information provided by human sources (*e.g.* human observations, reports, social media, etc.) has led to a demand for novel techniques for the fusion of information coming from heterogeneous sources, beyond conventional sensor-based raw data, in order to provide improved situational awareness and decision-making. While the processing (fusion) of information from hard sensors is widely covered within the fusion literature for years [5], the fusion of information from soft sources received only recently quite more attention [6], [7], [8]. Combining both types of information has also attracted increasing interest in the domain of Hard and Soft information fusion within the last years: [9], [10], [11], [12], [13], [14], [15] propose new methods, algorithms, frameworks, architectures and uncertainty alignment approaches.

In the context of multi-INT or hard and soft fusion, sources of information of various types need to be combined, which may require some alignment (*e.g.* semantic) especially in the case where sources do not speak the same "language" (hard vs soft sources). By characterizing sources of information, we aim at a better understanding of the underlying of the meaning of "hard" and "soft" information or sources [16]. Roughly, we have the idea that information coming from soft sources (*i.e.* humans) is subjective, qualitative, vague, unstructured, while information coming from hard sources (*i.e.* physical sensors) is objective, quantitative, structured. But things are not as simple since a human is able to provide numerical values or purely objective statements (such as counting the number of patients at the hospital emergency admission). A clear characterization of sources of information is important for information (and uncertainty) alignment. Indeed, since transformation or alignment processes usually result in information loss that could be avoided in firstly combining sources of the same nature.

A unified characterization of the sources of information along with quality dimensions support the fusion architecture design in which alignment steps are either minimized or better characterized. It is expected that this work will stimulate discussions within the Evaluation of Technologies for Uncertainty Representation Working Group (ETURWG) working group[17] to further detail the *Source* class as well as the associated *Input Criteria* class of the Uncertainty Representation and Reasoning Evaluation Framework (URREF) ontology [18].

The paper is organized as follows. In Section II, we first propose some observations related to the characterization and quality of sources that will shape the following discussion of this paper. In Section III, we propose a functional model of a source of information distinguishing between information container and information producer. Section IV proposes a structured list of dimensions along which a source of information can be qualified, and establish the links with some information quality dimensions. This description is intended to rely on standards while apply to both hard and soft sources. We illustrate some of the quality dimensions put forward on a practical experiment of light detection involving both automatic (hard) and human (soft) detectors in Section V. Finally, we conclude in Section VI and open on future steps of our work.

## II. Preliminary observations and challenges

To illustrate the different points of our discussion, we will consider the Vehicle-Borne Improvised Explosive Device (VBIED) scenario defined for the *Uncertainty Forum* organized by John Lavery and Simon Maskell [19]. This hard and soft fusion "micro-vignette" was used as a reference point for comparative discussions on some different ways of representing and dealing with uncertainty [19]. The story is summarized here (see [20] for more details): The concern is VBIED attack on an administrative building $B$. The suspect is an individual $A$ previously detected as having an unstable behavior. Two cameras positioned "near" and "far from" $B$ respectively capture images of the traffic. Two analysts (one experienced and one new in post) provide opinions about the presence of the suspect individual $A$ close to building $B$. An Automatic Number Plate Recognition (ANPR) system analyzing the video outputs of one of the two cameras also outputs some opinion about the recognition of $A$'s vehicle. Based on these sources, a decision maker should take the decision to evacuate or not the building. Three sources of information are identified: $S_1$, Analyst 1 (experienced), $S_2$, the ANPR and $S_3$ Analyst 2 (new in post)[1].

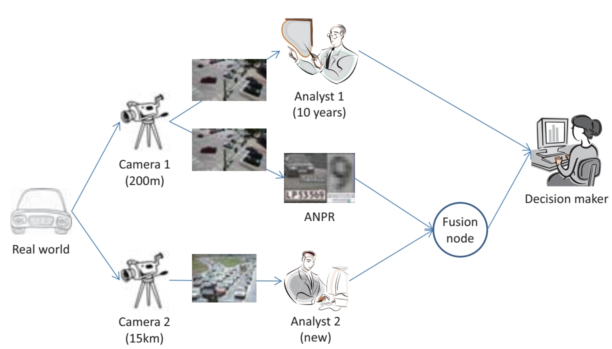


Fig. 1. Chain of information processing of the VBIED scenario from [19]. "Is $S_1$ more *valuable* than $S_2$ combined with $S_3$?"

[1]Some prior information is also available ("$A$ has unstable behavior"), thus a fourth source of information can be added as being for instance an automatic anomaly detector processing video output, or a witness having reported this abnormal behavior.

Within this general setting of a hard and soft fusion problem, we made several preliminary observations:

*1) Different source types:* D. Hall and J. Jordan [21] distinguish three pillars of sources, namely *S-Space* (physic-based sensors), *H-Space* (soft human observers) and *I-Space* (archived data and Internet). In this context, since a source output is usually being consumed by some human agent, we can add the notion of *Hybrid Hard/Soft* sources that corresponds for instance to hard data provided by physical sensors (*e.g.* image, video) annotated by human observers as a result of their interpretation of the sensed output data.

*2) Information container vs. information producer:* Generally, two types of objects are considered as sources of information: (1) *information containers* such as databases, textual documents, maps, images, videos, social media, web sites and data repositories, etc, (see for instance [22]) and (2) *information producer* such as radars or any physical sensor, but also human observers (experts, witnesses) or any automatic processor (classifier, anomaly detectors, etc). We should find a way to characterize all of them.

*3) "Source" is a relative notion:* The notion of "source" depends on the perspective at hand. In a general setting, information circulates within a network defining a chain of information processing from the physical world to some decision maker, who becomes a source of information for a higher level of processing. Nodes of this network are either named as "sources" (information producer), "agents" (information processor and actors), etc. For instance, in the scenario illustrated in Figure 1, what are the different sources of information? The two cameras? The images or videos provided by the cameras at different time steps? The analysts? The camera coupled with the ANPR system? In [23], the term *Provenance* is used to capture the entire chain of information processing. Since the primary task of an information source is to provide information, the source's quality will be assessed according to its ability to provide information. That means that the (possible) internal reasoning process will not be characterized in detail and we follow Steinberg stating that "[s]ource characterization [. . . is] concerned specifically with the information reporting performance, behavior and pertinent relationships of agents" [24].

*4) Source quality vs information quality dimensions:* The source quality (SQ) strongly relies on the information quality (IQ) it supplies. Indeed, a "good" source is the one providing "good" information. However, SQ does not equal IQ. Rather, the quality assessment of the information supplied by a given source over some period of time is *translated* into the source's quality. For instance, precision and accuracy are typically IQ dimensions (see definitions in Table I). The statistical joint assessment of precision and accuracy of the information provided by a source $s$ during laboratory tests can be translated into a perennial notion of *reliability* of the source, that is its ability to provide predictable results. The reliability factor can then be used to correct, alter, qualify the output information (by means of the uncertainty assignment $\eta$ introduced in Section III-B) but also as predictive parameters. Possibly, any IQ dimension can be translated into a SQ dimension: $s$ is credible if it provides credible information, $s$ is relevant if it provides relevant information, $s$ is objective if it provides objective information, etc.

It is not the purpose of this paper to detail the quality of a piece of information, a task that will be done in an upcoming publication. However the description of information quality we refer to in this paper is consistent with some standard ones, in particular the one of Klir and Yuan [25] for the self-content of information in the field of uncertainty-based information theory, the classical definition of accuracy, trueness and precision as defined by the international vocabulary of metrology [26], the reliability (of the source) vs the credibility (of the information) as defined by the STANAG 2511 [4], but also the classical work of Wang and Strong [1].

## III. Functional model of a source of information

We propose here a functional model of a source of information which aims at (1) covering the two aspects of sources of information as generally understood in the literature from the various domains (container vs. producer), (2) being valid for both hard and soft sources, (3) being detailed enough to identify the elements of source's quality but (4) rough enough to avoid the "trap" of a complete algorithmic description.

Firstly, we distinguish between an *information container* and an *information producer* which allows to consider them either independently or jointly. For instance, a witness (an information container) may produce different information, possibly of different quality, upon interview of Inquisitor 1 and Inquisitor 2 (two distinct information producers) or while liberally providing information on its own (joint information container and producer). Along the same lines, the same database (or Internet in general) may not return the same information using Search Engine 1 or Search Engine 2.

An advantage of this distinction is to better characterize the independence between sources, a concept central to the assessment of information quality (*e.g.* for credibility rating of information in the STANAG 2511 [4]) as well as to information combination (*e.g.* requirement for Dempster's rule of combination [27]). The dependence between sources of information (or by extension between pieces of information themselves) leads to data looping or incest which is a major issue in information propagation in networks (see for instance [28]).

Figure 2 illustrates the proposed model of a source of information that will be detailed in the following sections.

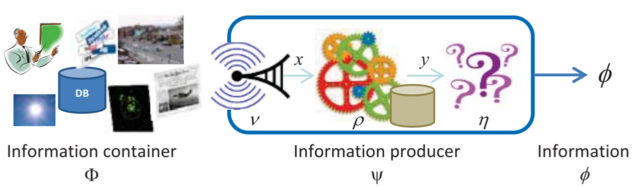


Fig. 2. Functional model of a source of information.

### A. Information container

Let $\Phi$ be an *information container* and let $[\Phi]$ be the set of all possible information containers. An information container is either a part of the real world (*e.g.* a scene, a vehicle, a group of people, a light emission, etc), either some abstraction of the real world (*e.g.* a track, an image, a video, a human generated report, a database, a map, etc, but also a situation, a link, a witness, etc). In the literature, these objects are sometimes referred to as "sources of information" (*e.g.* [22], [29]).

**Definition 1 (Information container)** *An information container $\Phi$ is an object from which some information can be gathered. A piece of information gathered from $\Phi$ will be denoted as $\phi$.*

We distinguish at this point the *object of interest* (denoted as $o$) from the *information container* since indirect observations are common (*e.g.* , estimating the presence of a specific individual $o$ through the observation of a video $\Phi$, estimating probability of occurrence of an IED event $o$ from records of past events in the area $\Phi$, etc).

An object of interest $o$ is characterized by a series of attributes $a$ among a set $\mathcal{A}_o$, such as the speed, the color, the length, the number of instances of a given keyword, etc. The range of each attribute is denoted as $\mathcal{X}_a$ which is the set of values possibly taken by attribute $a$. The real value of attribute $a$ for object $o$ is denoted by $a(o) = x^*$ (*e.g.* the speed of the vehicle is 100 km/h). In the case of a dynamic attribute, we will note $a(o)(t) = x^*$ as the value of attribute $a$ of $o$ at time[2] $t$.

### B. Information producer

Contrary to the information container, the *information producer* $\Psi$ has some perception and processing capabilities.

**Definition 2 (Information producer)** *An information producer $\Psi$ is a device with at least the 3 elementary functions of (a) observation (or perception, sensing) $\nu$, (b) reasoning (or processing, classification) $\rho$ and (c) uncertainty assignment $\eta$:*

$$\Psi = \eta \circ \rho \circ \nu$$

*An information producer is a mapping from $[\Phi]$ to $\Phi$, such that $\Psi(\Phi) = \phi$ is a (piece of) information gathered by $\Psi$ from $\Phi$.*

Applying a series of information producers $\{\Psi_n\}_{n=1}^N$ to a single information container $\Phi_1$ produces another information container $\Phi_2$ of possibly reduced quality, with filtered information, etc. For instance, a database ($\Phi_2$) is built from observations of the real world ($\Phi_1$).

**Definition 3 (Observation function)** *An observation function $\nu_a$ is a mapping from $\Phi$ to $\mathcal{X}_a^{(s)}$ where $\mathcal{X}_a^{(s)}$ is the range of attribute $a \in \mathcal{A}_o$ for object $o$ as measured by source $s$. $\nu_a(\Phi) = x$ is the measured or observed value of attribute $a$ of $o$ by $s$.*

For a given source $s$, we consider a series of observation functions $\{\nu_a\}$, $a \in \mathcal{A}^{(s)}$ allowing to gather information about

[2] In this paper, the superscript $*$ is used to denote the true value of a variable (*e.g.* $x^*$, $y^*$, ...).

attributes describing $o$, where $\mathcal{A}^{(s)} \subset \mathcal{A}_o$ is the set of attributes measurable (observable) by $s$.

The observation function is intended to be general enough to cover the cases of:

- automatic observations such as those performed by physical sensors or measuring devices, usually lively perceiving features of the real world, and
- manual observations such as those performed through queries by human operators upon databases or interviewing a witness.

These two types of observation functions are mainly distinguished by the frequency of their activation which is almost continuous and regular in the case of automatic observations while discrete and irregular in the case of manual queries.

**Definition 4 (Reasoning function)** *A reasoning function $\rho$ is a mapping from the measurement space $\mathcal{X}_a^{(s)}$ to a class space $\mathcal{Y}_b^{(s)}$ where $\mathcal{Y}_b^{(s)}$ is the range of attribute $b \in \mathcal{B}^{(s)}$ for source $s$. $\rho(x) = y$ is the output of some reasoning process performed upon some measurement $x$.*

$\mathcal{B}^{(s)}$ is the set of attributes possibly output by $s$. In the case where the source outputs information about its measurement, $\mathcal{A}^{(s)} = \mathcal{B}^{(s)}$. An example of such a reasoning process is the detection which, based on some measurements, outputs an estimated detection decision $y$. Another example would be the human reasoning process which, based on some perception of physical parameters such as the humidity, temperature or wind, possibly combined with some past experience, decides that it will rain within the next 3 hours.

**Definition 5 (Uncertainty assignment)** *An uncertainty assignment $\eta$ is defined over $\mathcal{Y}_b^{(s)}$ and acts as an alteration of the output of the reasoning function $\rho$.*

No specific format is defined for the uncertainty assignment function. It can be expressed in natural language (*e.g.* "I think that [...] up to a degree of 0.8"), as a discounting factor estimated from source's reliability, in terms of mathematical models for uncertainty representation, *e.g.* any fuzzy measure in the sense of Sugeno [30] which is a general structure encompassing the cases of probabilistic, evidential and possibilistic representations. It expresses the *self-confidence* of source $s$ regarding the result of its reasoning $y$.

**Definition 6 (Source of information)** *A* source of information *$s$ is defined as the couple $s = (\Phi; \Psi)$ of an* information container *$\Phi$ and an* information producer *$\Psi = \eta \circ \rho \circ \nu$, with the following relation: $\Psi(\Phi) = \phi$.*

Some of the functions composing the information producer $\nu$, $\rho$ or $\eta$ may be the identity function Id[3]. In particular:

- $\eta = \mathrm{Id}$ represents a source without alteration and which outputs directly the result of the reasoning function;
- $\rho = \mathrm{Id}$ represents a source which directly outputs the measured value with possibly additional uncertainty as assigned by $\eta$; thus in that case $\mathcal{X}_a = \mathcal{Y}$;
- $\eta = \mathrm{Id}$ and $\rho = \mathrm{Id}$ represents a source without alteration and which outputs directly the measured value.

We assume that $\nu$ cannot be the identity function.

[3]The identity function outputs the same value used as its argument.

## IV. Source quality dimensions

We rely on some standards from both hard and soft sources quality description (Sections IV-A and IV-B respectively) and merge the two types of criteria in Section IV-C resulting in a structured list for hard and soft sources quality dimensions.

### A. *Measurement properties of Semantic Sensor Network*

Among prior work aimed at characterizing hard data sensors and observations, the W3C Semantic Sensor Network Incubator group (the SSN-XG) produced an ontology to describe sensors in terms of capabilities, measurement processes, observations and deployments [31]. This ontology conciliates several existing ontologies and relies on standard definitions for uncertainty-related concepts in particular the International Vocabulary of Metrology (VIM in French) [26]. The object `MeasurementProperty` of SSN describes several properties of measuring devices (sensors) and is thus a very good starting point for an ontological description of a source of information. `MeasurementProperty` is defined as "An identifiable and observable characteristic of a sensor's observations or ability to make observations" [31] and has eleven (11) subclasses of properties (see Figure 3 reproduced from [31]). Some properties are *measuring (sensing) device* properties (*Resolution*, *Measurement Range*, *Sensitivity*, *Selectivity*, *Frequency*, *Latency*, *Response Time* and *Detection Limit*), while others are *(output) information* properties (*Accuracy*, *Precision* and *Drift*) translated into source' properties (See Table I for the definitions). These eleven properties are as many source quality dimensions which mainly address the observation function $\nu$, and we think that these eleven quality dimensions are valid for any information producer source as far as the perception is concerned, being it a physical sensor or a human. An example of instantiation of these properties for a hard source (camera) and a soft source (human observer) is given in Table II in Section V.

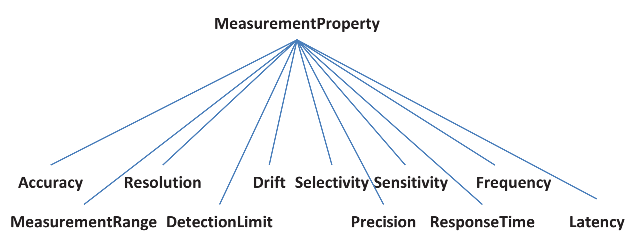


Fig. 3. Semantic Sensor Network `MeasurementProperty` class (reproduced from [31]).

### B. *Quality of human sources*

While the SSN ontology is a standard for physical devices properties, to the best of our knowledge, no such equivalent standard exists for human sources. Among the properties identified in the previous section some are missing, especially those addressing the cognitive aspect as represented by functions $\rho$ and $\eta$. Human performances are classified in [32] into the three general types of task network, cognitive and vision[4]. At the vision level, the use computational algorithms to simulate the human visual processing of an image is closely related to level 1 of Endsley and Garland's situation awareness (SA) model [33], *i.e.* perception of the elements in the environment, the first step in achieving SA. Cognitive level performances assessment are addressed by (human) sources rating scales as defined by standards in the intelligence community [4], [34] or in expert assessment procedure within the justice domain (*e.g.* [35]).

In the field of military intelligence collection, the STANAG 2511 (formerly 2022) [4] defines a scale of *reliability* rates from A to F for qualifying a source of information. This scale is rather qualitative with some ordering based on the main notions of *repeatability* ("Tried [...] source", "used in the past") and *accuracy* ("successful", "some degree of confidence"). Besides its lack of clarity, this scale proposes a global rating of source quality. Another 6-level source rating scale defined by the US Department of the Army for intelligence collection [34] relies on the notions of *authenticity*, *trustworthiness*, *competency*, *repeatability* ("history"), *accuracy* ("valid information"), *doubt*. This scale is more formal and clearer since all these notions appear in each of the rating levels (except F) which defines a better ordering. However, as in [4], quality factors are not defined.

In the field of justice and law, in order to assess experts quality in testifying in court, Gross and Mnookin [35] identify four "issues for consumers of expert information[5]" that we interpret as four dimensions for human source's quality: *validity*, *competence*, *clarity* and *bias*.

In [36], the concept of veracity is described along the orthogonal dimensions of *truthfulness* (vs *deception*), *objectivity* (vs *subjectivity*) and *credibility* (vs *implausibility*). Although the authors address quality of textual data, these dimensions are related to the sources and will be considered here as source quality dimensions. *Truthfulness* (or *deception*) and *relevance* are identified in [37] as two important characteristics of information sources.

### C. Consolidated list of source quality dimensions

Table I shows a unified description of information source's quality covering hard and soft fusion sources, bringing back together hard sources quality as described by the SSN ontology and soft sources as described by both intelligence sources' rating and expert quality assessment for court testimonies. We merged similar concepts when defined with different standpoints (either hard or soft sources) worrying of the exclusivity (no overlap) and exhaustivity (complete list) of the uncertainty-related concepts to sources' characterization. The list focuses on basic concepts (with no or hopefully little overlap) while compound concepts such as trust [38] or veracity [36] are not considered here.

[4]We are not concerned in this paper by the first type of task network which relates to human actions.

[5]An expert is "someone whose career is devoted to arcane information" [35].

In the forth column of this table, the elementary constructs of the source model concerned by the quality dimensions are identified. For instance, the *measurement range* is simply denoted as $\mathcal{X}_a^{(s)}$, the *frequency* is the lap of time between $\phi(t)$ and $\phi(t+1)$, *Subjectivity* can be seen as a case where neither $\nu$, neither $\rho$ nor $\eta$ is accessible to the receiver. *Truthfulness* is illustrated by $y$ being different from $\phi$ (the source does not supply all the information it has), etc.

## V. Illustration on a practical case

We illustrate in this section some concepts developed in this paper: (1) Three types of sources Hard, Soft and Hybrid (see Section II), (2) the link between information quality and source quality, (3) the camera and human characteristics as described by SSN.

A practical experiment has been conducted in Clermont-Ferrand LRPC fog chamber (see Figure 4) by INO (Institut National d'Optique in Quebec City, Canada). The fog chamber consists of a 31-meter long tunnel with a night tunnel and a day section. Fog is created with sprinkles, depending on the type of water, big and small drops can be created with varying density creating customized atmospheric visibility. Also, several visible and thermal sources have been positioned 27 meter away from both human observers and visible and infrared sensors.

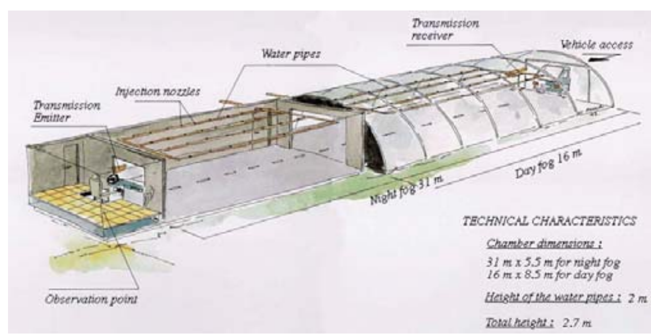


Fig. 4. Artificial fog chamber at the *Laboratoire des Ponts et Chaussées de Clermont-Ferrand*.

As illustrated in Figure 5, we will be comparing 1) the human performance looking at the emitter through fog (soft source only), 2) the sensor performance using a simple detection algorithm (Maximum A Posteriori) of the emitter through fog (hard source only) and 3) a human looking at the sensor capture, of the emitter and fog, via a computer screen (hybrid hard-soft source)[6].

### A. Experiment

The objective of the experiment is to evaluate the detection performance of visible and infrared sensors to identify a light emitter through variable atmospheric fog. The sensors have visible through far Infra-Red (IR) sensing capabilities[7], and the emitters (sources) comprise blackbodies, LED and

[6]Due to space constraints, the results of the last experiment are not included here but will be in an extended version of this paper.

[7]In this paper we only deal with the visible aspect of the experiment.

TABLE I
HARD AND SOFT SOURCES QUALITY DIMENSIONS.

| Source quality dimensions | Definition | Ref. | Elements of source model | Related concepts |
|---|---|---|---|---|
| Measurement range | The set of values that the source can return as the result of an observation under the defined conditions with the defined measurement properties | [26]* | $\mathcal{Y}_b^{(s)}$, $b \in \mathcal{B}^{(s)}$ | Resolution |
| Resolution | The smallest difference in the value of a quality being observed that would result in perceptibly different values of observation results | [26] | $\Delta_a$, $\Delta_b$ such that $[x_m : \Delta_a : x_M]$, $[y_m : \Delta_b : y_M]$ | Granularity |
| Latency | The time between a request for an observation and the source providing a result | [31] | $\Delta_t$ such that $q(t) \rightarrow \phi(t+\Delta_t)$ | Timeliness |
| Frequency | The smallest possible time between one observation and the next | [31] | $\Delta_t$ between $\phi(t)$ and $\phi(t+1)$ | |
| Response time | The time between a (step) change in the value of an observed quality and a source (possibly with specified error) 'settling' on an observed value | [26]* | $\Delta_t$ such that $\Delta_\Phi(t) \rightarrow \Delta_\phi(t+\Delta_t)$ | |
| Sensitivity | Sensitivity is the quotient of the change in a result of source and the corresponding change in a value of a quality being observed | [26]* | $\frac{\Delta_\phi}{\Delta_\Phi}$ | |
| Selectivity | Ability to provide observed values for one or more qualities such that the values of each quality are independent of other qualities in the phenomenon, body, or substance being investigated | [26]* | Independence of elements of $\mathcal{B}^{(s)}$ | |
| Truthfulness | Quality of the source of supplying the information it possesses | [37] | $\rho$, $\eta$; $y = \phi$ | Deception |
| Detection limit | An observed value for which the probability of falsely claiming the absence of a component in a material is $\beta$, given a probability $\alpha$ of falsely claiming its presence | [26] | $\rho$ | |
| Accuracy | Quality of providing an observation value in close agreement with the true value of the observed quality | [26]* | $\phi \leftrightarrow y^*$ | Bias (systematic error), Noise (random error) |
| Precision | Quality of providing replicate observations on an unchanged or similar quality value; ability to consistently reproduce an observation | [26]* | $\phi_1, \phi_2, \ldots, \phi_n$ | Reliability |
| Drift | Quality of providing a continuous or incremental, change in the reported values of observations over time for an unchanging quality | [26]* | $\{\phi(t)\}_t$ | Bias |
| Relevance | Quality of providing useful information regarding a given question of interest | [37] | Impact of $\phi$ on other $\phi_i$s | Utility |
| Objectivity | Quality of providing information regardless perspectives, experiences, feelings, beliefs, desires | [39]* | Accessibility of $\nu$, $\rho$, $\eta$ | Subjectivity |
| Self-confidence | Credibility of information as estimated by the source itself | [17] | $\nu$; $y \rightarrow \phi$ | Uncertainty |
| Field of expertise | Domains about which the source is able to provide information | | $\mathcal{B}^{(s)}$ | Competence |

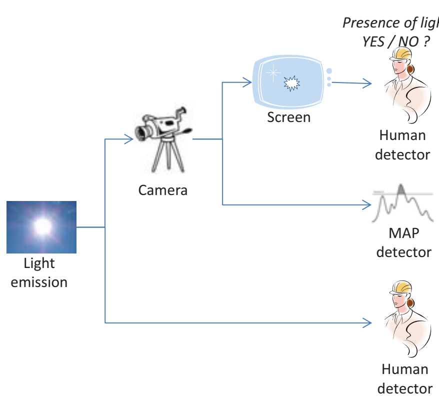


Fig. 5. Hard and soft sources of information for the light detection experiment.

incandescent lights. MTF targets were also employed in order to evaluate the point spread function (PSF) of the fog. The visible light consists of a Philips PAR38 LED comprising a diffuser and a pinhole, hence simulating a light much further away from the observation stand. The visible sensor (camera) is a Zyla sCMOS from Andor.

Our scene consists of an emitter inside a foggy atmosphere; the emitter is fixed, only atmospheric conditions change. A scene always begins with no fog, and then fog saturates the room at no visibility level, and dissipates gradually. Also a black curtain maximizing visual contrast is disposed behind the emitter to ensure only early vision tasks are involved (see Figure 6).

Fig. 6. Deployed target structure and camera box.

It is asked to the humans whether they detect a known light or not. The task does not need visual search of the source in a large viewing area against cluttered background. The line of sight is clear of any obstruction (glass, goggles) except fog. The test is conducted with no external light condition to mimic a night time observation. Humans were asked to wear adapted goggles prior to the observation to ensure that they eliminate the Purkinje shift effect or dark adaptation of the human eye and to be ready for a scotopic vision observation. The sensors took 100 acquisitions at 30Hz and a mean image was computed. A simple gray level threshold gave the detection algorithm for the source appearance in the image. From these results a confusion matrix was obtained as a performance measure for both the humans and the sensors.

Through this experiment, we aim at comparing hard and soft sources along the same subsets of the dimensions identified in Section IV-C. Because the real world observed is very simple (only a light to detect), the human reasoning part $\rho$ is reduced at its minimum. Also, the human is not allowed to assign some uncertainty after his/her decision and is required to provide binary answers (YES or NO). Moreover, the human is not supposed to lie or make any deception. Thus, the uncertainty assignment $\eta$ is also reduced at its minimum.

### B. *Hard and soft sources characteristics*

In order to compare similar characteristics and to predict source performances among several scenarios, a list of characteristics has to be established. A functional aggregation of those characteristics oriented to a specific task to accomplish will give a performance metric. One performance metric that is largely employed in pattern recognition is the confusion matrix from which measures of both *accuracy* and *precision* can be deduced. Characteristics can be established from a signal processing perspective, a computer vision, or psychological point of view. In any manner, they have to be representative of the performance (limitations and strengths) of each source. Skorka and Joseph [29] employ eight (8) signal processing characteristics to compare human eyes against different sensors, namely power consumption (PC), visual field (VF), spatial resolution (SR), temporal resolution (TR), signal-to-noise-ratio (SNR), signal-to-noise-and-distortion ratio (SNDR), DR, and dark limit (DL). In [40] the authors compare classification performances and therefore use a ROC curve. In Leiden [32] vision models are developed to predict human performance for target detection tasks, ORACLE by BAE the OptiMetrics Visual Performance Model, the Georgia Tech Vision Model and the CAGE eye model in [41]. The probability of detection, for accurately identifying a target, is common to all models.

Table II compares some SSN measurement properties from both physical sensor and human sensor (eye) standpoints.

TABLE II
ILLUSTRATION OF SOME SOURCE QUALITY DIMENSIONS RELATED TO THE OBSERVATION FUNCTION $\nu$.

| SQD | Physical sensor | Human eye |
|---|---|---|
| Measurement range | Dynamic range (DR) of the sensor depending on the target | Dynamic range (DR) of the eye is around 90db |
| Resolution | Spatial resolution (SR), smallest intensity value it can detect, depending on the target | Spatial resolution (SR) for a human eye is between 1 and 4.5 microns |
| Detection limit | Threshold to which a target is identified considering background noise; the smallest contrast measure to detect a target, relevant only (relevant only when an algorithm is added to the sensor) | The eye contrast limit may be 2% to 15% depending on an arbitrary limit |
| Response time | Two times the inverse of the frequency (according to Nyquist) | Two times the inverse of the frequency (according to Nyquist) |
| Latency | Time it takes to produce an image plus a target detection algorithm processing time | Between 100ms and 350ms for the eye only |
| Frequency | Temporal resolution (TR) | Temporal resolution of the eye, around 12 frames/sec but depends a lot on the emitter and background |

The detection algorithm is a simple threshold of raw images which removes all objects containing fewer than 10 pixels, fills any holes and connects those pixels. In Table III, the confusion matrix for source/camera/algorithm chain and source/camera/screen/eye chain are shown. It is interesting to see that the automatic detector tends to commit more often type I error (detecting more than one target) than the human. Because the algorithm detection threshold is constant, 20% higher than the noise level, it tends to produce false positives as two or more targets would appear from extremely low light reflections (see Figure 7). In the fog tunnel we did not include tests for true negatives, therefore this number is not evaluated, but we believe that since the tunnel reproduces night conditions, no light would contaminate the observation and therefore the true negative rate would be high. When humans look at an image taken from the camera, with no algorithm enhancement but just only a print screen, they tend to commit a high rate of type II error. False negatives appear because sometimes the 8bit resolution makes the subtle light contrasts disappearing from the 16bit image of the camera.

TABLE III
ACCURACY AND PRECISION AS REPRESENTED BY CONFUSION MATRICES.

Source-Camera-Detector

| | |
|---|---|
| 36% | 64% |
| 0.2% | NA |

Source-Screen-Human

| | |
|---|---|
| 62% | 0% |
| 38% | NA |

Fig. 7. False targets detected by the algorithm from low light reflections.

## VI. CONCLUSIONS

In this paper, we proposed a description of a source of information along with a series of dimensions that we consider as basic for further source's quality assessment. The formalization proposed considers the intrinsic features of the source as they influence the information output. We proposed a functional model of a source of information generic enough to cover the wide range of varieties of sources of information as it is understood in both hard and soft domains. We identified the basic properties or characteristics of both hard and soft information sources along which the source can then be qualified. We then derive a consolidated list of properties for hard and soft sources quality dimensions. The idea is to conciliate in a single model the description of both hard and soft sources, and to establish a list of dimensions as much exclusive and exhaustive as possible. We illustrated some properties on real data gathered from experiment involving both automatic and human detectors, showing the meaning of these properties for both sources.

As further work, a deeper description of information quality and its link to source quality is required. This work is in line with the uncertainty modeling efforts of the ETURWG group and will contribute to the enrichment of the URREF ontology.

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