Image-Object Retrieval in Mixed Information Systems: Theory behind the Practice

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Abstract

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The retrieval of image data in information systems that are both global and open-ended cannot be advanced independently of the way that image-data objects are generated, processed and stored in those systems. A universal representation is needed compatible with other types of multimedia data and fully integral at the human-computer interface. Instead of imposing common standards, impossible in such an environment, a natural universal reference form is sought as a basis for understanding the general principles of image retrieval. To this end formal categories may be constructed of image-data objects and their complex structures. It is argued that all image forms are representable in the same general pullback category enabling the universal operations which can form the basis of all practical image activity.

Keywords: IR theory and models (general); architectures for IR systems; theoretical discussion of the information seeking process; image indexing/retrieval; metadata for retrieval of non-text information.

1 Conceptual Representation of Image Data

Image data techniques need to provide a technology to interrogate distributed data by naive (end) users in open-ended generalised information management systems. Image processors cannot afford to develop independently of the other components in multimedia information systems and it would be a loss to bypass the experience in information retrieval, databases and human-computer interaction learnt in the last three decades. Ideally image storage and retrieval should be performed in a manner that is a simple extension and merger of current work in these areas for integration and for use in and across a variety of operational data situations. This is a very wide span from business, commerce and the professions, through scientific, engineering and medical applications to the world of culture and the fine arts. There is also a need to have transparent cross-platform use of the same images for data visualisation and virtual reality as well as in related specialised fields [1]. There is also a link with cryptography through the art of stenography and water marks [20].

The development of universal principles in image processing would help prevent fragmentation into a myriad of inconsistent methods and standards. We should therefore be looking for general underlying principles that can form the basis of natural standards to be found within, not imposed from without.

This is a difficult requirement for image-data objects where complex data structures may need to be matched in open-ended systems with connections between heterogeneous models. In standard data technology it is assumed that all data can be represented in a standard character code such as ASCII. This principle can be carried over some way with image data as found in the use of Postscript. However image data in analogue form is so varied that a piece-meal approach can only lead to a plethora of incompatible competing subsystems. There is a need for the simplest basic format maintainable over long periods across different systems. Hardware advances mean that a virtual infinite bandwidth storage capacity are available

[1] like opto-electronics [5], holographs [13, 15] and artificial vision with neuromorphic vision chips [23].

so that earlier procedures for elaborate coding methods, including compression, are no longer needed as they may be only a hindrance to global communications and the future persistence of image data for later generations.

A proper universal approach is needed from the outset. This has always been the rationale underlying database models but traditional models like the hierarchical, network, and the relational (including SQL) may not be adequate for components involving pictorial as well as textual data. There are fundamental differences in that additional levels become necessary and at each level there is an extension of typing. To be reliably universal the theory needs to be formal. However even mathematical theory has to be implementable and computable. This leads to the requirement for the use of constructive mathematics where recent results in category theory appear very pertinent to the formal philosophy of image representation and retrieval.

Category theory provides a way to handle image objects consistent with parallel developments in areas like signal processing, data warehousing, data mining and data fusion. The latter for the commercial environment seeks to integrate fully all the information for a particular business. Image data is now an important component needed to enhance the performance of many decision-making procedures in mixed systems. Examples range from robotics to subjects like medical diagnostics, and even financial market analysis.

Category theory is a very convenient mathematical workspace to bring together all the relevant techniques and the wide range of specialised methods and tools available. Examples found in the literature of particular methods that need to be integrated include uncertainty-based methods [11], inductive query languages [17], genetic algorithms, simulated annealing, rule induction [1], neural networks, data migration, intelligent agents [21], inference agents, reverse patching [27], case similarity for retrieval [12]and re-use [44] as well as methods borrowed generally from signal processing like wavelets[2], chaos and fractals, time-frequency waveform representation and other image transforms[3], linear/non-linear and robust

[2]used to distinguish texture in contents-based retrieval [34]

[3]for example fourier, karhunen, loeve, haar, hadamard, hough, walsh and singular-value

filtering, markov random fields [25][4], gibbs distribution, stochastic optimization, as well as tomographic reconstructions. These methods are applicable to image enhancement and restoration, multi-resolution processing, scale and colour spaces, edge detection, texture and shape analysis, remote sensing and industrial inspection. Human processes are often modelled[5].

Image objects therefore provide quite a challenge and methodological leap for the subject of information retrieval in mixed-information systems. The technology has progressed far beyond the physical document and we are well into the concept of the logical document as a complex abstract structure and process. As indicated above it is the number of levels that have to be handled and their inter-relationships. It is comparable to the difference in text retrieval between syntactically (more or less physically based) searching on controlled keywords through semantically significant free vocabulary to the richer pragmatics of full text in context. An analogue picture is a much more compact form of information communication than its digital counterpart. It is that distinction that category theory can capture. Earlier forms of discrete mathematics such as set theory have the same limitations as the digital image format. Searching on images is a value-added activity requiring more sophisticated methods.

There is great current interest in the object-oriented approach[6] which has been used to structure meta-information for image retrieval emphasising the composition of visual entities [38] [7] and in the use of objects for visual agents in portable computing interfaces [21].

From this wide-ranging list of current applications, it is clear that image retrieval has to be applied to a very wide range of activities. Text retrieval like standard database technology has been developed

decomposition

[4]For similarity matching of chromatic and spatial information using rough-picture queries [25].

[5]For instance Yasuda et al [46] used a human memory model, involving graceful oblivion and abrupt recollection, as it is claimed that pyramidal (ie hierarchical) coding provides better comparison efficiencies.

[6]However, there are problems in unifying the separate set theoretic approaches to the object-oriented methods on offer [4].

[7]where the entities like human, chair, etc are distinguished from their respective constituents like eye, leg, etc.

in the context of the stand-alone database with local well-defined rules, a simple local universe with control vocabulary etc. Search engines attempt to extend these same methods for distributed data rather than to reconsider the complexity afresh from basic principles. Image processing involves not only the manipulation of large volumes of data at the syntactic level but also an attempt to understand the semantic features portrayed by the image to a viewer. For example, colour photographs held in an image database in the `tif` format or `JPEG` may occupy 10Mb each of storage space but users would like to scan them for the presence of certain features such as the presence of colours in a particular pattern. The system will need highly efficient disk handling routines plus sophisticated means of analysing images. The number of applications is immense[8].

To satisfy all these demands, image retrieval systems may be interpreted through a viewer with varying contrasts, highlights and brightness. The techniques to perform this are usually numerical algorithms based on continuous mathematics. The techniques are analagous to data mining in so far as display patterns and data fusion are being investigated.

2 Current State of Image Representation

There have been two main directions to date in handling image data [14] :

- Image contents can be modelled as a set of attributes to give a fairly high level of abstraction but with little scope for free or ad hoc queries [18, 30],
- Feature extraction/object recognition subsystems provide an automated approach to object recognition but the methods are difficult, computationally expensive and tend to be domain specific [40].

[8]The number of digital cameras sold by 2001 is expected to be 8m every year in the USA compared to 2m now. There are 2 billion photographs taken each year in business and ten times that amount if personal use is take into account [42].

Rather than employ general models as used in databases (relational, network and hierarchical), information retrieval has traditionally employed customized methods (for example relevance matching or ranking algorithms). Text retrieval tends to be performed by specialised packages, usually involving inverted files. SPIRES [36] was an early example of the use of a generalised database management approach to information retrieval which used quite an advanced form of dynamic data modelling which was particularly fitted to complex documents in full text (for example, like UK Statutes). Comparable database systems are now needed to store image data that can be searched with queries at the intensional level. Based on the experience of text retrieval, customized systems for similarity based image retrieval using only relevance feedback techniques of IR may be too simplistic unless they can extend to the extra layers of metadata to be found in database systems.

It is to be noted that there is a prominent use of text to assist searches in the systems based on attributes like Chabot [30]. Text is extensively used to support image retrieval. Text may be used in this way because of the natural adjointness between text and image data which will be discussed below. For instance facial images using textual qualitative descriptions are described by Srihari [40] as mentioned above. See also Picard & Minka's work reported in 1995 [32].

The current state of text retrieval systems now can be seen in systems like Strudel[8, 9] to deal with web-based text.

In technical terms, the theoretical problems on image processing crystallise as follows:

- there is an emphasis on powerobjects rather than atomic objects with flexible searching required on clusters and groups;
- universal relations need to be constructed to make new connections intra-schema (local universe) and inter-schema (global universe) - i.e. for integration of images with text across heterogeneous databases;
- type/domain resolution is necessary to recognise which attributes

are joinable - for different types of image representation (pixel, graph, Postscript)

Categories provide a theory of types. Typing is an inherent feature of every image recognition and therefore a necessary part of image retrieval. There are two basic categories to type image data. These are:

1. the source of the data ;
2. the medium of the data.

Thus for an old master the source will be a human painter (of a certain character e.g. a genius like van Gough which will be reflected in the painting and may therefore form part of any search criteria), whereas the medium may well be a painting in oils which will again import certain characteristics to the image and be specifiable in the retrieval process. A computer-generated image from automatic methods could have a source like natural physical processes in meteorology or natural biological processes in medical applications. These two examples might today very well be in some medium with similar characteristics. Both have bit streams but still have different types for their respective sources. These full typing features need to be available to the system as necessary for storage, retrieval, display, etc. There is an adjointness between the two categories as discussed below. A review of current methods shows the diversity of aims and requirements of the many applications of the use of image analysis, particularly as indicators of physical states and phenomena and therefore the complication for compatibility and integration.

3 Current Application Areas

There is no limit to the variety of potential applications of data images. Typical examples of the importance of their detailed use can be seen in the speed sensor microwave imager for predicting long-term rainfall [7] or in the special sensor microwave imager [43]. In utilising the information to be derived from the images to predict long-term rainfall, there is a need to distinguish nonraining background conditions from any direct emission or scattering from the hydrometer. Similarly remote viewing with multi-spectral images allows 'nowcasting' of fog and pollution hazards but there is a need for image retrieval to take account of noise in either the source or the medium [43]because thermal emission in the near infrared has to be eliminated. However, colour is often an important distinguishing feature. In the latter it can help to detect whether rain is present or not [16].

A comparable need to extract information from the details of images and the corresponding rigorous requirements for precise query specifications are to be found in medical image applications. However, medical information systems themselves tend to consist of a great proportion of image information of an imprecise nature. The knowledge extractable from the imprecision may be quite critical but cannot be so easily identified as in textual information. Content-based image retrieval is needed for computer-aided diagnosis and [41] is an example of a system that uses object-oriented iconic queries to gain access to the information at the semantic level by association through prototypes. Other contents-based retrieval used in medical imaging employ type abstraction hierarchies [17]. Images may be classified by an automatic clustering algorithm and shapes and spatial relationships derived from object contours but they always have a dependence on specific knowledge of the image domain.

Standard fixed forms are also in use for medical diagnosis [31] but only it seems at the storage level. R-trees used to index points in a multidimensional space can distinguish unexpected objects (for example, tumors and hematoma) from expected objects like hearts and lungs as a diagnostic tool.

A facet of information retrieval that does not feature much if at all in document retrieval is texture. These are perceptions of *qualia*[33]. Notice the difference between the search for a portrait with a mature use of colour and a colour portrait of a mature face. Both involve qualia, the former at a syntactical level and the latter at a semantic level. Nevertheless despite difficulties texture because of its importance is already being used as a search criterion. For instance with human faces in [6], facial images have been shown to be distinguishable by a small number of relevant stimulus parameters based on the results of psycho-physical research.

In [26], the perception of human texture is resolved into the three components of periodicity, directionality and randomness. Picard & Minka [32] compare human texture with searching on texture of water in digital libraries. They suggest that no single model is sufficient. Shakir & Nagao [38] therefore use a selection of models to represent texture such as meta information, the hierarchical model and the object-oriented approach.

Some work on semantic interrogation has been carried out by Yang & Wu [45] who propose a query-by-example diagrammatic language using type constructors like functions and inheritance to manipulate images at the semantic level.

This has been no more than a cursory survey of current activity in image work but it is perhaps sufficient to show the need for fundamental studies if the subject is to proceed in a coherent scientific way that can encompass the many different facets of the subject. It is for this reason that in investigating the universal requisites for image representation that we have had to turn to the modern mathematics of category theory.

4 Brief Review of Category Theory

Categories of identity arrows (objects) and arrows are formally related by functors and functors by natural transformations so that category theory only needs the concept of the arrow as a transitive transformation of these three types (arrows, functors, natural transformations). An important result follows that any number of levels beyond four are redundant for a full description of any system.

Category theory is able to unify many standard mathematical ideas which are needed in information processing [3] for a knowledge engineering context and in particular for objects like graphs, semantic nets, geometric models and hierarchies, as used in image work[12].

It has also exposed to view concepts that were hardly recognised previously. One of the most important of these new concepts is adjointness. Adjointness is a fundamental universal property showing itself in many forms in a wide variety of situations but whose general nature has only really been appreciated in the last twenty years, particularly in the context of the contravariant relationship between intensional and extensional data [24]. By virtue of the adjoint functor theorem[10], left adjoints preserve colimits (right-exactness) and right adjoints preserve limits (left-exactness). Colimits are the dual of limits. Text at the word level is the simplest of examples; searching at the semantic level is more sophisticated but the principles remain the same except that we have to deal in categories rather than sets.

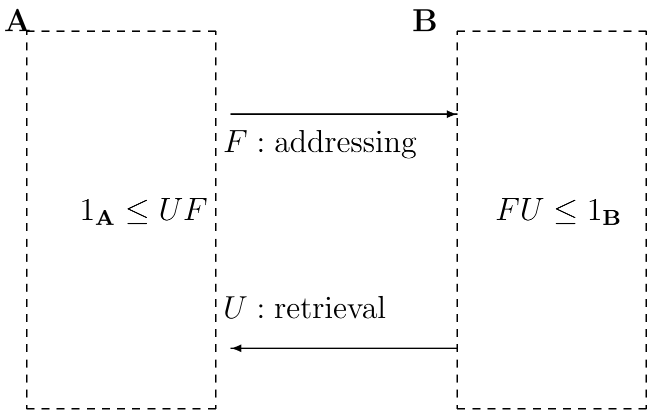

Figure 1: Adjointness in Indexing

Adjointness is a characteristic of all forms of indexing. Its general nature in category theory terms can perhaps be understood in the example of the indexing of a traditional book. The simplest index is an inverted file (concordance), an example of pure adjointness, $F \dashv U : \mathbf{A} \longrightarrow \mathbf{B}$. The ordering in the book of category $\mathbf{A}$ is the order of the words of natural language. The indexer has complete free choice on how to index but subject to the initial ordering of $\mathbf{A}$. The arrow is the free functor F describing a particular choice of indexing, for example on words, concepts, chapter headings, figures, etc. Category $\mathbf{B}$ contains the ordering of the index, the simplest form is usually a lexical order of the important words in the text with the page numbers on which they appear. This is a totally free ordering in **B** but entirely subject to the ordering in **A**. A reader uses the order in **B** to find the page required in **A**, an operation of the underlying functor U. With this information the reader finds the required page leaving the index (with its own ordering) behind showing that U is also the forgetful functor.

If category **A** is a collection of multimedia objects, the arrows would be the relationships of conceptual links with higher-order arrows relating collections such as documents. The free functor F is the (arbitrary) addressing for each multimedia object in the collection. This formal theory of indexing in the adjointness of two categories is illustrated in Figure 1.

Notice that $1_{\mathbf{A}} \leq UF$ consists of all the orderings in the text and $FU \leq 1_{\mathbf{B}}$ all the orderings in the index. Therefore the underlying functor $U : \mathbf{B} \longrightarrow \mathbf{A}$ provides the overall awareness of the contents of the documents in category **A**. The awareness of these can be retained with a more elaborate database management model. The index need not be fixed. For example [22] uses a parallel and distributed associative network to focus directly on any subset of pixels in the image with a method from optical holography. This enables dynamical indexing avoiding ad hoc predetermined fixed indexing. [47] examines the efficiency of indexing for image and video databases at four levels (pixel, nearest neighbour, block and full image) to construct a generalised histogram as a phase space for their invariant properties of translation, rotation, reflection and connection. Now we need the counterpart of a dynamic index for distributed multimedia data.

4.1 Adjointness between Text and Image Data

The relationship between different forms of representation of data, particularly the intensional-extensional correlation, is fundamental to all applications such as the manipulation of image data based on content and meaning. Imaging is rapidly becoming a major industry and a burning research topic to be seen as part of a much wider field of study of information engineering. They all follow the same pattern as the adjointness between textual and image information where both are mapped onto the electronic medium as a bit stream.

Multimedia are logical rather than physical based. They are an abstract category of a document which may be represented as a textual file or as an image file resulting from input by means of a scanner. The two forms clearly contain equivalent information although they would appear in quite different electronic forms. This is an important example of adjointness as demonstrated in Figure 2. $\mathbf{TXT(X)}, \mathbf{IMG(D)}$ and $\mathbf{ELE(2)}$ are categories corresponding respectively to text, image and electronic form. Each of these categories is a free functor. In set theoretic terms $\mathbf{TXT(X)}$ is a map from the alphabet X on to finite strings so a character, x, goes to a string, $x \mapsto <x>$. $\mathbf{ELE(2)}$ is correspondingly composed of strings of zeros and ones. $\mathbf{IMG(D)}$ provides a definitive visual form which might be available in words in $\mathbf{TXT(X)}$. The transformations

$$\mathbf{IMG(D)} \rightleftharpoons \mathbf{TXT(X)}$$

will not be lossless but are both subcategories of some greater category. Thus the human imagination of a reader of text may supply features not available in the image form and the converse also holds.

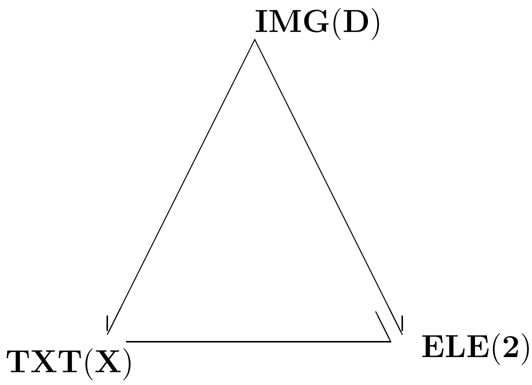

Figure 2: Adjointness of Electronic Forms

4.2 Intension-Extension Mapping

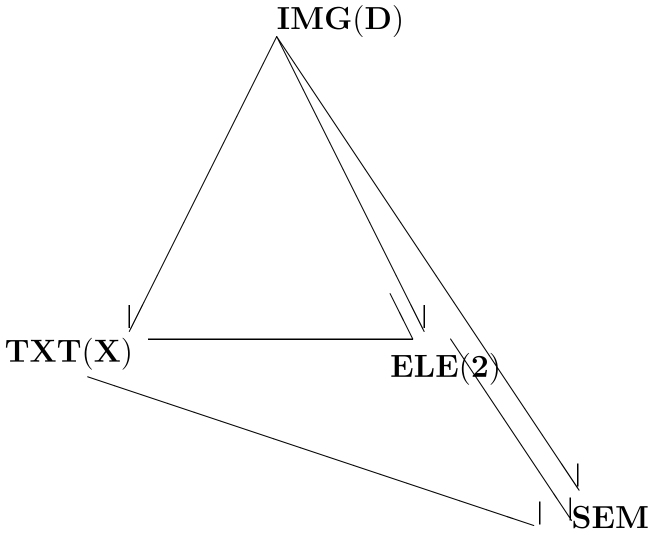

Figure 3: Adjointness in Real-world Semantics

The links in multimedia may therefore be at different levels. The mappings representing the links would therefore need to be typed in geometric logic. There is the simple linking between documents like a citation of a label or name (the intension). A more powerful level of connection is within the semantics (the extension). There is also the intension-extension relationship which has been shown by Lawvere [24] to be composed of adjoint functors.

The extension level of the abstract document is therefore the same for the three categories of text, image and the electronic bits of the digital form. Equality in geometric logic is provided for by composition. The possible relationships between the three categories of documents at the two levels can therefore all be summed up in a simple geometric formal diagram.

A real-world semantics **SEM** can be represented in any of the three forms of image, text and electronic. There will therefore be intension, and extension consisting of contravariant functors between each of the three and **SEM** as in the diagram in Figure 3.

It is this adjointness that enables images to be retrieved by the use of linguistic descriptions. An image database may therefore be interrogated by any of the ordinary textual query methods to retrieve facial images like the use of controlled vocabulary or often more simply the use of rough queries. More advanced textual methods are also in use such as those to retrieve facial images using fuzzy sets[11]. Fuzzy-set theory has been used too in a fine-arts database to input impression words of different degree for the location and other semantic features, for example, the query 'joyful pictures which have a mountain in the center and there is a tree in the right' [29].

5 Image Retrieval

One important concept from sheaf theory is the pullback or fibred product where a product is restricted over some object or category. $\mathbf{S}$ and $\mathbf{M}$ both have arrows to some common category $\mathbf{W}$ (the real-world) as $\mathbf{S} \xrightarrow{f} \mathbf{W}$ and $\mathbf{M} \xrightarrow{t} \mathbf{W}$, and the subproduct of $\mathbf{S}$ and $\mathbf{M}$ over $\mathbf{IMG}$ written as $\mathbf{S} \times_{\mathbf{IMG}} \mathbf{M}$ may be represented by the diagram shown in Figure 4.

The diagram in Figure 4 describes the pullback of t along f. The product $\mathbf{S} \times_{\mathbf{IMG}} \mathbf{M}$ is an example of the universal limit. Holographic methods are examples of exploiting the concept of limit [22]. It seems in general that the discovery of knowledge, as in information retrieval, is always the pullback of an arrow along another arrow over some category. The pullback limit is technically *left exactness* [10]. This is the formal description of the existence of any knowable entity in the real world.

$$\begin{tikzcd}
 & \mathbf{S} \arrow[dr, "f"] & \\
\mathbf{S} \times_{\mathbf{IMG}} \mathbf{M} \arrow[ur, "f^*(t)"] \arrow[dr, "\epsilon_f(t)"'] & & \mathbf{W}/\mathbf{IMG} \\
 & \mathbf{M} \arrow[ur, "t"'] &
\end{tikzcd}$$

Figure 4: Pullback of t along f

This example shows well the difference between the use of universal theory in constructive mathematics and the axiomatic set theory style of SQL where a kind of brute-force has to be applied to extract exact knowledge as a member of the powerset. The better scientific approach is to conceptualise from the three-level standpoint of this example. Thus all images are the limits in the pullback of two categories, a source (**S**) and a medium (**M**). The category **W** contains a subcategory **IMG** consisting of the real-world components that make up the source and the medium. These are real-world constructions. Again the important relationships between these indexed partial-orders are those of adjointness which lead to a formal understanding of the query. There is the need to find universal forms because they are natural; they should also be obvious and are usually quite trivial to identify.

The pullback diagram is actually richer than that shown in Figure 4. As indicated in Figure 5 many other arrows are in fact involved. Because of the principle of adjointness, these are unique which is why a particular arrow can imply that an image object exists and, if it exists, it can be retrieved by the appropriate query.

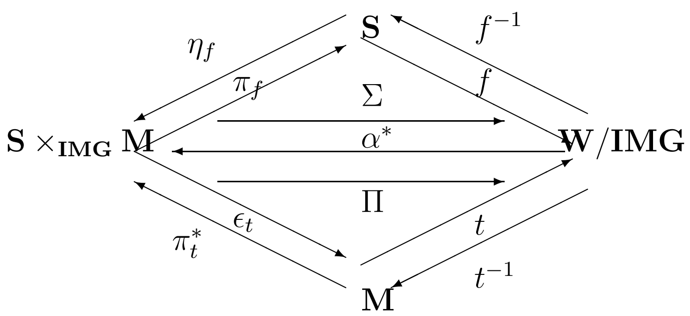

Figure 5: Pullback of source type t along image type f showing fuller collection of arrows

The nature of these further arrows, together with those already introduced, is shown in the table in Figure 6.

arrow	selects	of	from	comment
f	W	given	S	source analysis
f^{-1}	S	given	W	source construction
t	W	given	M	medium analysis
t^{-1}	M	given	W	medium construction
π_f	S	given	$S \times M$	source nature
ϵ_t	M	given	$S \times M$	image *qualia*
α^*	$S \times M$	given	W	real-world image query
η_f	$S \times M$	given	S	image creativity
π_t^*	$S \times M$	given	M	medium type
Σ	W	some	$S \times M$	component collection e.g. pixels
Π	W	all	$S \times M$	component combinations

Figure 6: Table showing nature of each arrow in Full Pullback Diagram in Figure 5

6 Application to Image Processing

Consequently the pullback diagram in Figure 5 can be applied to the universal problem of image representation. The universal categories for any image are source **S** and medium **M**. For example a painter would be an object in the category **S** and oils an object in the category **M**. For subcategory **S** painter and subcategory **M** for oils, the limit $\mathbf{S} \times_{\mathbf{IMG}} \mathbf{M}$ represents all the paintings by different painters and **W** includes particular components of the oil medium. For computer-generated images $\mathbf{S} \times_{\mathbf{IMG}} \mathbf{M}$ where the category S represents computers, **M** is the electronic medium and **W** consists of hardware items ranging from the components of the distributed IT systems to the pixel representations i.e. the arrows, of the categories $\mathbf{S} \times_{\mathbf{IMG}} \mathbf{M}$ and **W**, each have a partial order self-indexed by their own semantics.

The arrow f maps each source on to forms of representation. t gives the forms used in a particular medium; this arrow performs the role of insertion of the category of medium into the physical or hardware form. The pullback (limit) $\mathbf{S} \times_{\mathbf{IMG}} \mathbf{M}$ contains all the components that make up the image forms. This is the generalised version of the familiar vector method and Salton's cosine [35, 39] which is an inner product. The limit $\mathbf{S} \times_{\mathbf{IMG}} \mathbf{M}$ is the outer product and the generalisation of the vector method and tensor products.

In general the arrow

$$\alpha^* : \mathbf{W}(\mathbf{SEM}) \longrightarrow \mathbf{S} \times_{\mathbf{IMG}} \mathbf{M}(\mathbf{SEM})$$

is the functor formally representing the discovery of knowledge in an operational sense. The table sets out the interpretation of the various arrows based on their universal form in category theory. Note that because of the three-level architecture, the highest type of arrow, natural transformation, can represent characteristics like creativity (η_f) or qualia (ϵ_t).

7 Concluding Remarks

Systems that are open like modern distributed information systems are exposed to real-world complexity. For instance [19] computer vision algorithms have from the outset had to accept the challenge of heterogeneous real-world systems. It matters not whether it is from the smallest lithograms of nanotechnology [28], or partial images of footprints to identify shoes in investigation at the scene of a crime [2], or constructions obtained from virtual telescopes to produce images greater than the diameter of the earth [37]. In each case it is necessary to get a handle on the complexity. Already we are seeing the appearance of products like JetSend from Hewlett-Packard to replace all drivers with one piece of code that enables any information appliance to talk with any other. Such interactive devices capable of cross-platform operation need to be constructed according to open-ended standards. It is to be noted that despite the extensive international standard on offer, present world-wide information interchange depends only on two basic standards for Communications:

SS7 (signalling system 7 for digital telephony) and TCP-IP for the internet. These simple standards are inadequate for the complexity of digital images.

John Taylor, IEE president 1998/99, sums up the position well [42]:

> For the last 30 years, computer science has focussed heavily on programming, function, compilers, etc. In comparison, data, databases, distributed information management etc have been rather second-class subjects with relatively little formal methodology or theory. From now on, the pendulum is going to swing rapidly the other way driven by storage technology, digital multimedia, the internet and WWW, informal information and personal digital imaging.

It is the formal theory in modern formulations like category theory that can provide the basis for open-ended natural standards that can cope with the required complexity.

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