A Dual-hierarchy Semantic Graph for Robust Object Recognition

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ABSTRACT

We present a system for object recognition based on a semantic model graph, which it can learn automatically from image examples. This model graph is based on intrinsic properties of objects such as structure and geometry, so it is more robust than the current machine learning methods that can be fooled by changing a few pixels. Current methods have proved to be powerful but fragile because they ignore the structure and semantics of the objects. We define semantics, or abstraction, in terms of the intrinsic properties of the object, not in terms of human language, so it can be learned automatically. Our model graph is more versatile than previous ones because it uses two distinct hierarchies: parts and abstraction. Previous semantic networks used only one amorphous hierarchy and were hard to build and traverse. Our system performs both the learning and recognition by an algorithm that moves in both hierarchies at the same time, combining the advantages of top-down and bottom-up strategies. This reduces dimensionality and obviates the need for the brute force of “big data” training.

Keywords: object recognition, ATR, semantic network, machine learning, modeling, abstraction, invariance

1. Introduction

In recent years the computer vision field has come to be dominated by methods of machine learning (ML) adapted from generic artificial intelligence. These methods do not have much specific understanding of images and rely on extensive training from given examples. These methods are relatively easy to apply and to show some success with, but they do not provide a reliable object recognition solution. The problem is not their immaturity; it is a fundamental limitation due to high dimensionality and non-linearity as we shall discuss later. Much more success has been achieved in sub-domains such as face recognition and license plate reading where specific knowledge has been applied but this is hard to generalize. In the following we describe the problems with current ML methods. We then present our way of applying general shape analysis to provide a general purpose, inherently robust system for representing and recognizing objects.

The challenges of object recognition stem from the high variability of observed objects. Among the many variables that affect images are viewpoint (pose), scale, illumination, occlusion, articulation, shadows, camouflage, sensor noise, etc. This is in addition to variability in the object itself, before even taking the image, such as when a vehicle is dented or damaged, has added or modified parts, has paint or dirt stains etc.

The common methods of machine learning try to combat the variability by training the system with a large set of known images or “templates.” Given such training, the system tries to recognize an unknown object based on the training images but without trying to understand the object on a more conceptual level. While this has resulted in success in several areas, the more general problem of variability has not been overcome. There are simply far too many variables to deal with just by the “brute-force” method of adding more training.

Another problem with current ML is fragility or brittleness. Changing just a few pixels in an image may be unnoticeable to the human eye but can result in a totally wrong identification by the ML system. Driverless cars have been known to miss a stop sign because there was a little sticker on it. Of course one can add training on stop signs with stickers but it is not possible to train for every possible variation.

It has been recognized [7],[9] that the way to improve the performance of any ML algorithm is to use domain-specific knowledge, namely specific understanding of the particular domain we work on, which in our case is the domain of
vision. In other words, we need to advance the study of shape analysis which seems to have fallen out of favor lately. If ML methods outperform more analytic methods in some cases, it does not necessarily mean that we can dispense with shape analysis altogether. It only means that we have to do a better analysis. The success stories in vision involve such specific knowledge in some sub-domains. For instance, face recognition under controlled conditions of pose and illumination can be done now without knowledge about faces, but when trying to go beyond these constraints, it was proved useful to include some modeling knowledge of faces in terms of “landmarks” such as eyes, nose and mouth [14]. The performance of “ignorant” ML methods degrades as we remove more constraints from the query images and general-purpose recognition is currently out of reach of these methods.

Shape analysis in terms of higher level visual concepts can improve the recognition performance for general images as well as solve the fragility problem. Moreover, it will give us insight of what the machine is actually doing. With present methods we have no understanding of how the machine makes decisions or why. This frustrates our intellectual curiosity and defies our long and prodigious experience of applying the scientific method. Even more importantly, we do not want to relegate important decisions to a machine with opaque decision-making. This is even more important in areas other than vision such as defense, finance or law.

Our system applies knowledge pertaining specifically to the vision domain. At the same time this knowledge is general within the image domain, being based on intrinsic properties of shapes. This enables our method to combine high-level semantics with low-level image processing in both representation and recognition, and to be independent of the source of the image such as EO, IR, LIDAR, LADAR etc., or even CAD drawings.

The contributions of this paper are as follows:

• A dual hierarchy representation. Many different hierarchies were used before to analyze shapes but they were all one dimensional, such as scale space, DCT etc. We show that such hierarchies are not sufficient to represent even the simplest objects such as polygons. We use two independent but interlocking hierarchies: an object’s parts and its level of abstraction. Previous semantic networks typically conflate these two hierarchies into one. These are in a way orthogonal to each other in our method and are traversed differently. Current (analysis-free) ML methods use hundreds of hierarchies which are parallel and are processed in the same way. It is hard to understand what they represent.

• A computational definition of abstraction, independent of human language, and specific to vision. (We use the term abstraction interchangeably with semantics, meaning, generic and sometimes invariance). The definition is based on parts of objects and the geometric relations between them. As these are intrinsic properties of objects, this makes the classification of the objects more robust. Our algorithm can figure out the semantics of an object from only a few examples. For instance, in Figure 6 we have circles and line segments in certain positions and orientations relative to each other. When the system sees a few examples of this group, it will give it a name which we can interpret as “face”. The smaller circles will be given names which we can call “eyes” and the big circle becomes “head”. In this way the system assigns “meanings” to the circles depending on their context.

• An algorithm of traversing the graph. Previous semantic networks were quite disorganized and difficult to traverse. Our algorithm moves in the two hierarchies simultaneously. Going up in the parts hierarchy (grouping) is similar to a traditional bottom-up strategy, while going down in the abstraction hierarchy is akin to a top-down strategy. We show that this combines the advantages of both while avoiding their pitfalls.

Our two-dimensional hierarchy is rich enough to represent a full variety of objects. Moreover, both our hierarchies represent the intrinsic geometry of objects and their relations with their parts rather than a general parameter such as scale. The parts hierarchy is based on object parts, e.g. a truck has a cabin, a trunk, wheels etc. The abstraction hierarchy includes generic objects on different levels, e.g. a vehicle is more abstract than a truck, a rectangle is more abstract than a door. (This is different from “levels of detail” as we shall see.) Current ML classifications, their version of abstractions, are probably too fragile to build a hierarchy of them. As our definition of abstraction is based on the structure and geometry of the objects it can be made reliably into a hierarchy.

An abstraction hierarchy is important even in recognizing very specific objects or “fingerprinting”. A user wants to know if a specific object seen in the image, say “a blue SUV with a dent on the right door”, already exists in the database. The object may be there already, but most likely observed from a different viewpoint and with different illumination. We thus have a high-dimensionality search that current methods have difficulty handling. Our recognition
algorithm will go down the abstraction hierarchy to recognize a generic SUV and then recognize the specific dented variant.

Semantic networks have been studied extensively in the context of general artificial intelligence. They usually derive their semantics from human language or perception. They often have a one dimensional hierarchy and make no distinction between parts and abstraction hierarchies. Google’s “knowledge graph” [6] is probably the biggest. Formal properties of such networks have been studied in [8]. Applications to vision are described in [2],[3],[5],[13]. They often use graph matching which we do not. An earlier version of the current ideas appeared in [12].

2. Limitations of template-based methods

Template matching is the most basic method of trying to recognize objects. Current ML methods share with template matching the property that the training images, or templates, are regarded as nothing more than a collection of pixels and no attempt is made to analyze the images in terms of higher level concepts. The templates are classified on the basis of their pixel content. A query image is put into one of the classes based on its pixel content. There are serious problems with these pixel-based methods:

- **Huge space of templates.** The space of simple binary 100x100 templates has 10,000 dimensions with $2^{10,000}$ possible templates, far more than any computer can ever handle. The “curse of dimensionality” makes it hard to go even beyond 2 dimensions, let alone 10,000.

- **Templates belonging to the same object are not necessarily close in template space.** Any classification method based on nearest-neighbor or compactness of classes in a template-based metric (as ML methods are) will fail much of the time.

The large template space manifests itself in practice by large variations of templates, belonging to the same object, resulting from differing viewpoints, scales, illumination, shadows, occlusion, articulation, noise etc. In addition there are variations in the objects themselves such as a myriad kinds of vehicles, as well as paint, dents etc. Figure 1 (left) shows some of the possible variations.

Furthermore, some representations of the object are so far from each other that they don’t share even one pixel with each other. In the example below, the two representations of the object have the same scale and viewpoint. Yet they are very far apart in any pixel-wise metric. Humans easily recognize the similarity but an ML system trained on templates will probably not. This suggests that human visual understanding is not simply a result of training on templates.
Machine learning methods try to handle the difficulties in two main ways:

- **Brute force**: using hundreds of millions of images coming from “big data” databases to train the classifier on.
- **Using methods of statistical inference to reduce the dimensionality of the search space and help the classification.**

Brute force by itself will never succeed in capturing the full variety of images even with the biggest data sets. There are simply too many variables that can change as discussed above. Thus all methods use some kind of statistically-based classifiers.

Most classifiers have some elements in common: a metric that measures distances between class members, a statistical assumption on the probability of these distances, and a non-linear element that affects which class the object belongs to. For example, in line fitting the metric is the distance of data points from a line, the assumption is that the distances are normally distributed random errors, and a non-linear function decides which data point is an outlier. Many statistically-based methods have been used in vision: Bayesian networks, support vector machines, principal component analysis, Markov random fields, k-nearest neighbors, minimal description length and many others. The current ML methods also contain the above elements in one way or another.

These methods are quite generic and they don’t have much understanding of the structure of objects or images. They typically use pixel-wise metric and assume some random error in this metric. However, looking at Figure 1, it is obvious that the pixel-wise distance between these two pictures is not random error. There are systematic differences there that cannot be captured statistically. The various variables involved influence the image in a non-linear way. Shadows or gray levels depend non-linearly on the positions of several unknown light sources, projection from 3D depends non-linearly on an unknown viewpoint. Thus the distance between objects is very different from the distance between the corresponding images. Objects can be close in the object space and far apart (pixel-wise) in the image space, and vice versa. The boundaries of the classes greatly differ in the two spaces in a complicated way. Current ML methods try to bridge this difference by a combination of linear smoothing filters and generic rectifying functions. This often fails in unexpected ways such as in overfitting, or seeing differences between objects where there are almost none in the images.

We can improve on this basic method by applying some knowledge about images. In the example of Figure 1, we know that edges matter more than pixels in recognizing objects, so we can use an edge detector on the real image on the left. This would make it much closer to the drawing on the right. Of course edge detectors have their own problems so we have to apply further knowledge like corner detection, points of interest, etc. to make the images closer.

This example is a special case of a general theorem that characterizes the performance of ML methods as applied to various problems. It is known as the NFL (No Free Lunch) theorem [7],[9]:

**Theorem (NFL): Any two search algorithms are equivalent when their performances are averaged over all possible problems.**

This means that we are unlikely to improve performance by tweaking some ML algorithm that was applied before or using a variant of it. Over a large set of problems, the performance levels of all these algorithms will converge to the same level. Given the difficulties of ML in high-dimensionality non-linear problems, this performance level leaves much room for improvement.

In other words, we have to “earn” our lunch and improve performance by using specific knowledge about vision rather than generic statistical assumptions. We cannot take the easy route and rely on a statistical machine learning method to do the task of image understanding. We have to use methods of shape analysis to obtain a true understanding of the structure and relationships of images and objects. Although ML methods outperformed systems that use analytic knowledge in some cases, this does not mean that we can eschew knowledge of vision altogether as is the current trend. It only means that we have not applied this knowledge correctly.

In the following we will apply knowledge of the shape and structure of objects and images to recognition and learning. Our distance metric is based explicitly on the features and structure of the objects. Our non-linear decision function is based on a positive feedback between the object, its parts and other related objects.
3. The dual hierarchy

A good way to reduce the dimensionality of a search is to use a hierarchy. Many kinds of hierarchies have been tried: scale space, wavelets, “pyramids”, quadtrees, Fourier transform, discrete cosine transform, parts decomposition, levels of detail, semantic levels, etc. The idea is that the higher levels of the hierarchy have lower dimensionality so recognizing objects becomes much easier. Once an object is recognized at a higher level, the information can be used to perform a more refined recognition.

All these methods have one problem in common: they are one-dimensional hierarchies. That is, there is only one parameter that changes as we go up the hierarchy, such as scale or level of detail. However, one dimension is not enough to represent the wide range of possible objects with all their variability. A simple example can demonstrate this. A polygon can be decomposed into parts, namely its sides. In a parts hierarchy the sides are lower than the polygon. The number of parts can distinguish different polygons from each other, e.g. a triangle, a quadrilateral, or a pentagon. However it cannot distinguish a generic quadrilateral from a rectangle, and a rectangle from a square. These are distinguished from each other by an independent hierarchy, involving geometric relations between the parts of the object. A rectangle is more specific (less generic or less “abstract”) than a quadrilateral as its angles are specified as all equal, and a square is more specific than a rectangle as all its sides are also equal. We can see that both of these hierarchies, the parts and the abstraction, are essential for describing even these simplest of objects. The hundreds of hierarchies used in current ML are obviously redundant for this example.

More real-life examples abound. A generic, or “abstract” vehicle is composed, in the parts hierarchy, of generic parts such as wheels, a body, doors, windows. A generic wheel is composed of a rim, a tire, a hub and spokes etc. In the abstraction hierarchy, a generic vehicle has more specific vehicles on a lower level of abstraction, such as a car, a truck, an SUV etc. These have similar parts but with different geometric relations. Similarly a car can be further specified as a sedan or a sports car etc. Generic wheels can be specified into types on a lower level of abstraction by geometric properties such as the thickness of the tires, the shape of the spokes, etc. Thus the two-dimensional hierarchy of parts and abstraction is quite sufficient to represent quite complex examples like these.

In the following we generalize these examples and use a dual hierarchy for our representation of objects:

- A parts hierarchy, in which objects are composed of simpler parts and those are made of yet simpler parts.
- An abstraction hierarchy, in which “abstract” also means “generic” as opposed to specific. This is different from levels of detail. A rectangle has the same number of details as a square but is more generic.

Both the abstraction and the parts hierarchies derive from the intrinsic nature of the object itself rather than from some general parameter such as scale or frequency. Thus these hierarchies are invariant to various changes in the environment such as changes in illumination or viewpoint as well as changes in the objects themselves such as paint or dents. Non-intrinsic parameters such as scale are not only not invariant but can distort the shape. For instance, a scale space hierarchy is generated by smoothing an image by (e.g.) a Gaussian filter. A limited amount of smoothing may be useful for some noise reduction but when taken too far it totally distorts the shape. A rectangle will lose its corners and gradually morph into a circle, an unrelated shape, as we go up in scale space.

4. What is an abstract object?

Abstraction, as philosophers have pointed out, is the process of finding generalities among specific things, or finding quantities that are invariant among several specific objects. (We define specific objects, in the context of vision, as ones represented by pixels.) Such abstract objects can be further abstracted at a higher level. Thus an abstract object can be defined as a class of objects, specific or abstract, with common properties. The abstraction process is usually done by humans using human perception and language. Here we use abstraction principles that can be applied computationally without human intervention. This abstraction is based on the intrinsic structure and geometry of the objects, so it makes the classification more robust. That is, the similarity or distance between objects is defined based on their structure and geometry, not on pixels. We obtain such abstractions by several means:

- **Geometric constraints.** Looser geometric constraints mean higher abstraction as they are common to a larger set of objects. Given a set of specific triangles, we can drop the specific lengths or angles of the sides and only
keep the property that it has three touching sides. This property is common to all specific triangles and is invariant to the lengths, thus defining an abstract triangle. In the example of the rectangle and square above, we used the geometric relations between parts, such as their relative sizes or angles. The square requires equal sides and angles. Dropping this specific requirement, we obtain a rectangle which only requires equal angles and is thus more abstract. In Figure 6 (right) an arrangement of circles and line segments is seen as an abstract “face”. This happens because reasonably loose geometric relations between those objects are common to many faces.

• Context. The abstraction or “meaning” can change according to the group the object is found in, namely the context. A circle can be an eye in the context of a face and a wheel in the context of the vehicle. In Figure 4, using knowledge specific to the face group, the big circle acquires the specific meaning of a “head”, the small circles are now “eyes” and the line segments are a nose and a mouth. Thus these parts acquire specific “meanings” through the context of a group they are parts of. Both the eye and the wheel are abstract, generic objects but at a lower level of abstraction than a circle as they are more specific than it. We treat a circle and an eye as separate objects in the hierarchy even when they are related to the same set of pixels in the image, because the eye is a part of the face group while the circle is not.

In the simple rectangle example, Figure 5, we first recognize the rectangle by the relations between line segments in the image. Given that, these line segments becomes “sides” of the rectangle, namely more specific objects than line segments, through their being parts of the rectangle. The rectangle can become a “window” in a context of a house, namely a group containing several rectangles, or a face of a box as a part of a 3D box.

• Parts. An object having generic or abstract parts implies an abstract object. In Figure 4 the generic face is made of generic eyes, mouth, etc. A truck can have a generic cab and a generic trunk as parts. Changing the kind of cab will not change its nature as a generic truck. This is illustrated in Figure 3. The generic truck (top left) is made of the generic cab and trunk (top right). The generic cab is connected to more specific cabs (bottom) which the generic truck does not know about.

In all the cases above the parts and abstraction hierarchies complement each other and we obtain a form of an intersection between them. We could not have distinguished the different abstract objects such as a circle and an eye without the parts hierarchy.

Other kinds of abstractions may be useful but were not used in this paper. For example the polygon is higher than both the triangle and the quadrilateral as the number of parts of a polygon is not specified. This may be of use more verbally than visually.

5. The graph representation

The question immediately arises of how to represent the dual hierarchy of parts and abstraction. Parts decomposition is quite easy to represent. However, how do we represent an abstract object such as a generic triangle? This seemingly simple problem has occupied philosophers since Plato. No one has ever seen a generic triangle – all the triangles we have ever seen are specific, having specific values for the lengths of the sides. Yet we do have a concept in our minds of an abstract, generic triangle. Obviously we have the verbal definition of a triangle, but this will not work for more complex objects such as vehicles. All the vehicles we have ever seen are specific vehicles, but we do have a concept of a generic vehicle. An exact verbal definition of a generic vehicle seems impossible for such a complex and variable object. Philosophers have argued for millennia whether abstract objects even exist in the world or they are only concepts in the mind (the “problem of universals”). In our method an abstract object exists as a node in a graph, connected to nodes of more specific objects. The generic triangle is depicted graphically in Figure 2. A truck example is in Figure 3.

In the following we describe a graph, or a network, that represents generic as well as specific objects with all their variations. This graph is organized as a dual hierarchy that represents both our parts and abstraction hierarchies. All objects, specific and generic, are represented as nodes in the graph. Their relations to each other are represented as links in the graph. Various graph and network methods have been tried before, but they never had the clear distinction between parts and abstraction hierarchies we use. We do not presume to know if biological vision systems are organized this way but it is easy to imagine that such a network can be built from neurons.
A simple example is shown in Figure 3. In this figure, a generic truck and two specific trucks with their parts and all known variants are represented in the same graph. The parts hierarchy is shown here left-to-right, i.e. a truck is made up of a cabin and a trunk as seen on each horizontal level. The abstraction hierarchy is shown vertically. At the top-level of this hierarchy, a generic truck node is linked horizontally (i.e. in the parts hierarchy) to a generic cabin and a generic trunk nodes. Similarly, on the lower abstraction level, the specific “truck1” and “truck2” are linked horizontally to the specific nodes of their respective parts, namely specific cabins and trunks. Our generic truck node is linked vertically to both the specific “truck1” and the “truck2” nodes lying at the lower abstraction level. Similarly, the generic parts, the cabin and the trunk at the top abstraction level, are linked vertically to more specific nodes of cabins and trunks at the lower level. (Objects that are at the same position in both hierarchies are arranged on diagonal lines that can represent a depth dimension. They are not linked to each other.)

A specific instance of an object can also be seen as a small sub-graph that includes the node of the object itself, its specific parts’ nodes, and a node for a corresponding generic object (Figure 3). This helps represent variants of an object. While each known object is represented by a node, variants of the same object do not need a separate node. We can have an object “truck1” (Figure 3) with two variants, containing either “cab1a” or “cab1b” as a part. The subgraph highlighted in the figure contains the parts of the specific variant. Thus the graph can represent many more variants of objects than the number of nodes it contains. (We can separate the variants into different objects with specific nodes if we want to.) This is useful as it would be quite hard to account separately for every possible variant of every possible object.

This example shows that the graph provides a very flexible definition of objects. We are not restricted to one definition of the “truck1” but we accommodate different variants having different variant parts, and we can also place them all as sub-graphs under the generic truck. Thus a large class of specific objects can be organized very economically as sub-graphs in the dual hierarchy under the same generic object. At the same time the graph remains understandable.

A general model graph includes objects from the very simple such as edges, corners, or line segments, to mid-level features such rectangles or circles, to the highest levels of objects to be recognized, each object having a position in each of the two hierarchies. In this way we integrate the high-level knowledge about structure and geometry of objects with low-level data.

Another example, Figure 4, illustrates context-dependent abstraction. A circle can be an abstraction of a wheel, an eye, or a head, all having different semantic meanings derived from the group they belong to. Thus the node “circle” is connected to the “eye”的s, the “head” and the “wheel” nodes which are at a lower level of abstraction. The eyes and head acquire their meanings by being parts of a face, while the wheel becomes so by being a part of a truck. Accordingly, the “eye” and “head” nodes are connected to the “face” node higher in the parts hierarchy, while the “wheel” node is connected to the “truck” node. The circle node is not connected directly to the face node as different circles in the face have different meanings (eyes, head). All these “circular” objects are assigned different nodes in the graph, and are distinct from the corresponding sets of pixels in the image. (Obviously they are all more abstract than these pixels.) Thus our graph affords us a very flexible representation of semantic knowledge as defined in Section 4.

The “circle” node represents an abstract circle and not the perfect circles shown in the drawing. It is impossible to draw a generic circle as all drawn circles are specific. The generic circle can be connected to more specific circles with various distortions, gaps or noisy data.
In addition to the objects, we need to represent the relations between objects and/or parts. These are represented by the links between the nodes. The relations can be geometric, e.g. distances, angles, relative sizes of parts etc, or they can be topological, e.g. a part touches another one or is contained within it. Topological relations are inherently invariant to geometric transformations such as viewpoint changes. We want our quantitative geometric relations to be invariant too. Distances and angles are not generally invariant, so we replace them as much as possible with quantities that are invariant. These include parallelism, symmetries and ratios of lengths. A graph is said to be “attributed" if the links between the nodes possess some quantitative properties, or “attributes". Thus our representation consists of an attributed graph containing object nodes and their attributed links.

The graph representation, being intrinsic to the objects, is invariant to external influences such as viewpoint or illumination changes, shadows etc. It is also invariant to the platform – whether we use EO, IR, LIDAR, LADAR or a CAD model so we can use the same representation. Thus it can be used as a form of a unified dataset of objects across all modalities. This can be useful for unifying the existing datasets of so-called “semantic levels”. These are related to but not the same as our levels of abstraction. These are currently separate datasets, e.g. a dataset for raw data, a dataset for polygon models, etc. We can represent them in a unified way in the same graph.

Figure 3: The dual-hierarchy graph. Recognized objects are highlighted.
6. The recognition algorithm

The graph containing all models is constructed off-line and serves as our dataset of models. Given an object to recognize, we now need to search for the correct model in the graph hierarchies. The dimensionality of the search is reduced by the two hierarchies.

Traditionally there are two competing approaches to traversing hierarchies: top-down and bottom-up, each with its own serious problems. Starting at the bottom, there are many raw features such as edges and we face a combinatorial problem of how to group them in the right way to obtain the higher level object. This is greatly compounded by noise and uncertainty in the features. Trying to start from the top, we have to somehow guess which high level object we might have and try to fit it to the low level features. We don't often have such a guess. In addition, it is not always clear if an

Figure 4: Model graph of a face.
objective is a high- or low-level object. Given a circle, it can represent a whole object such as a face or a small part of it such as the pupil of an eye.

Our dual hierarchy makes it possible to use both strategies at the same time, combining their advantages and avoiding their problems. In a nutshell, we use a top-down traversal in the abstraction hierarchy and bottom-up in the parts hierarchy. A circle is both a low-level primitive in the parts hierarchy, e.g. the pupil, and a high-level abstraction in the abstraction hierarchy, such as the face. Thus a circle can be a starting point for both hierarchies (Figure 7).

Another problem with traditional methods is that they try to build an image graph separately from the model graph and then match the two. For example, they try to find edges, lines, circles, etc. with no knowledge of what the object is and then try to match these parts to the model. This often fails because the visible lines or circles are often ambiguous and cannot be reliably detected until the object itself is recognized. In our algorithm building the image graph is directed by knowledge from the model graph and not by some generic heuristics. Thus building the image graph is in effect equivalent to the recognition algorithm.

The recognition algorithms proceeds using two processes:

- **Generation of grouping hypotheses**: bottom-up in the parts hierarchy. Given some detected objects in the image, with detected geometric relations, we use them as “clues” to find a suitable hypothesis. We typically only need two such objects. We look them up in the model graph to see if there is a group there that contains these objects as parts with the given relations. For example, if we detect two line segments that touch each other at a right angle, we check the model graph and find the group “rectangle” which contains such line segments as parts. This is a group hypothesis. (Figure 5.) In the example of Figure 6 the clues are a pair of circles and a line segment in certain relations, which lead to the hypothesis of a face, with a suitable coordinate transformation. Of course this is only one hypothesis and we have to check many more. The number of hypotheses can be limited by heuristics such as proximity in distance or angle (parallelism).

- **Verification and specification**: top-down in the abstraction hierarchy. For a hypothesized group, we look up its parts in the model graph and check if there are corresponding objects in the image. If so then the hypothesis is verified. These parts typically have meanings within the group which are on a lower level of abstraction than the corresponding objects we already found in the image, so we add them to the image graph under the corresponding objects we found. In the above hypothesis of a rectangle, we find in the model graph that a rectangle has four parts with certain relations and so we look for them in the image. Finding four corresponding line segments verifies the rectangle hypothesis. We add the node “rectangle” to the image graph at a higher level in the parts hierarchy (with appropriate connections). Of course this is only one hypothesis and we have to check many more. The number of hypotheses can be limited by heuristics such as proximity in distance or angle (parallelism).

We iterate similarly to the next levels. We can see from these examples that the image graph is built incrementally using knowledge stored in the model graph. As the recognized objects are represented by the image graph, building the image graph constitutes recognition. No graph matching is involved.

Figure 5 illustrates the iterative process. The red lines represent the hypothesis generation and the green lines represent the verification. Dotted lines represent failed hypotheses such as a “square”. Successful hypothesis nodes are highlighted in yellow and are copied to the image graph. As described above, we start from the “linseg” nodes (line segments) and hypothesize the “rectangle” node with the grouping process. The verification process verifies this node and creates the “side” nodes under the “linseg” nodes, with appropriate connections, as the sides are more specific than line segments. The rectangle is obviously higher in the parts hierarchy than its sides and is at the same level as they are in the abstraction hierarchy. In this way the algorithm moves one step up in the parts hierarchy and down in the abstraction hierarchy.

In the next iteration we apply the grouping process to the rectangles and create the “box” hypothesis. (There can be many rectangle nodes in the image graph while there is only one in the model graph.) The 3D projection is taken into
account when checking the relations between the rectangles that make up the boxes. The verification process finds the “box-face” parts of the box and places them under the corresponding “rectangle” nodes.

We proceed in a similar way to more interesting objects. In the next iteration we check if the boxes have the right geometric relations to group them into a “truck”. The verification and specification process then find the “cab” and the “trunk” parts as specific meanings of the corresponding boxes that generated the truck hypothesis, so these nodes are added under these box nodes. The node “truck” in the model graph is linked to additional parts such as wheels and bumpers, so we try to locate them in the image. A “wheel” node is then placed under a “circle” node in the abstraction hierarchy if one is present in the image. This further verifies the “truck” hypothesis. In the next iteration we use more specific relations between the cab and the trunk of the truck to find the more specific “truck1”. We add this node to the image graph. The failed hypothesis “truck2” is not added.

The relations used for hypothesizing are stored in the same hierarchical graph structure. For example, the specific relations for hypothesizing truck1 and truck2 are stored in the generic truck node and do not need to be checked when looking for specific faces. The initial hypotheses relations are in the “top” node.

The face example is shown in Figure 7. We start from two similar circles and one line segment found in the image. Given their geometric relations, we hypothesize a face in the model graph, Figure 4. Figure 7 shows the image graph that we built. The eyes, mouth, nose and head were verified in the image, so the face was verified. The ears were not verified.
In summary, we go up in the parts hierarchy and down in the abstraction hierarchy at the same time, simultaneously grouping parts and recognizing more specific objects. This process is directed through all levels of the processing by prior knowledge, stored in the model graph hierarchies. This avoids errors such as noise and shadows because these are not present in the model graph.

7. **Propagation of probabilities**

Unlike pixel-based methods, we measure distances between images of objects in terms of the distances of the corresponding nodes of the graph. This takes into account the structure and geometry of the objects. Each object in our system has a coordinate system with an origin and principal axes. The axes represent the orientation and size of the object. Distances between nodes include the differences of the origins of the objects as well as their axes.

Each node we create in the image graph is assigned a probability for its existence. The probabilities propagate through the graph in a way somewhat similar to a Bayesian network. However, unlike a Bayesian network, we allow some back propagation. This can create some feedback loops, so we structure the back propagation in a way that prevents this. Thus the probability of an object depends on its structure, i.e. a set of nodes connected with that object’s node such as in the sub-graph in Figure 3.

All the relations between nodes expressed in links of the model graph, such as relative positions or orientations, are expressed with elasticity, or as “springs” with constants that represent the tolerances of these relations. When building the image graph these relations are usually not satisfied perfectly, so we use the elastic strain as a measure of the conditional probability of one node to exist given the others. Obviously the conditional probability is lower when the deviation of the relations from the model is higher. Maximizing the probability means minimizing this deviation, or our distance measure, of the image graph from the ideal model.
Each step in the recognition algorithm above creates a bunch of nodes. We update the probabilities of nodes in an iterative process that takes into account the probabilities of all nodes connected to a particular node as well as the conditional probabilities in the links. Only the most elementary nodes such as edges are connected by “springs” to the raw image data. All nodes can move on their connected springs. The goal is to update the positions and axes of the objects so that the overall probability is maximized.

- For every new node created in the image graph, sum the probabilities contributed from all the nodes linked to it, namely the other nodes’ probabilities times the conditional probabilities expressed in their links.
- For every old node connected to a new one, update its probability using a similar sum, this time including the new nodes. Then proceed to update nodes connected to that node. We take care to avoid feedback loops. Stop updating when a node is more than twice removed from the new node.
- For each new or updated node, adjust its position and axes to maximize the overall probability.
- Iterate until convergence.

This algorithm provides a non-linear decision function that is based on the intrinsic structure of the object. The probability of a truck in the image is increased when we also recognize the cab and the trunk and vice versa. A line segment that looks faint in the image may be interpreted as side of a rectangle. The connections of this rectangle to other sides strengthens this interpretation, and this in turn will further strengthen the rectangle. When the faint line segment is not connected to anything, its interpretation is weakened and it is deemed noise. This feedback between nodes is useful, as long as it is supported by other connected nodes and is not a result of a feedback loop.

8. The learning algorithm

Since our definition of “abstraction” does not depend on human language, our learning algorithm can be fully autonomous. The algorithm uses its own rules of abstraction to learn from sample images as discussed in Section 4. Our learning algorithm is analogous to the recognition algorithm described above: we go up in the parts hierarchy by grouping simpler parts, and simultaneously we go down in the abstraction hierarchy from generic to specific objects. Using the two hierarchies reduces the dimensionality of the learning, avoiding the “big data” training of current ML methods.

Unlike current ML methods, we start from some knowledge embedded in the system. This takes the form of:

- A set of simple model shapes such as line segments, circles, rectangles, boxes, etc. we place them at the bottom of the parts hierarchy and at the top of the abstraction hierarchy.
- A set of functions expressing relations between shapes, e.g. distance, angle difference, lengths ratio.
- A set of rules for building the dual hierarchies.

We proceed using processes similar to the recognition algorithm and akin to the scientific method:

- **Generation of grouping hypotheses.** Looking at the given images, we look for instances in which simple objects are at certain relations as measured by our relation functions. For example the system may see two boxes that are at certain distance and angles relative to each other. (A box is a basic shape which the system can already recognize.) If it sees this arrangement multiple times, it generates a hypothesis of a possible object which it may call a “truck”. Statistically, we look for arrangements that are not explainable by a random distribution and hypothesize them to be probable objects.

- **Verification and specification.** The system checks the sample images to see if there are other objects similar the hypothesized “truck”. If this happens consistently then the “truck” is considered a verified object. An appropriate node is added to the model graph. New nodes for “cab” and “trunk” are added as its parts under the corresponding boxes in the abstraction hierarchy, with appropriate connections. The “truck” node is higher in the parts hierarchy and on the same level in the abstraction hierarchy as its parts. It may find circles in certain positions under the “box”’s that gave rise to the trucks, so new nodes “wheel”’s are added under the corresponding circles in the abstraction hierarchy. We have thus gone down in the
abstraction hierarchy and added nodes which are more specific than the boxes and circles. The system notes the distributions of the values of various relation functions between the parts of an object and uses them to assign the mean values and elasticity constants of these relations.

In the initial step the relations are quite loose and inclusive to fit a high-level abstraction of a truck. In the next iteration the system learns to differentiate between the specific “truck1” and “truck2”. The system looks at several trucks in the images and checks the relations between parts of the trucks, such as distances or size ratios of the cab and trunk. It finds that these quantities do not follow a random distribution but some relations values occur more frequently than others. It assigns one set of frequent values as “truck1” and the other as “truck2”. It adds these nodes under the “truck” node in the abstraction hierarchy, which thus becomes a generic truck.

The iteration stops when all variations in the image can be explained as random errors. Then the distance between images of the same object is reduced to random error, unlike the pixel-based metrics. This is possible only because we use the structure and geometry of the objects.

Biologically, one can speculate that certain generic objects are built into the vision system. For instance, a generic “predator” is built into our brains because it would be too late for the victim to learn this from examples. Specific predators such as “lion” and “tiger” can be learned later from examples. Mythical monsters in movies or cartoons can look even scarier than real creatures even though we have never seen their likes before.

9. Implementation

The method has been implemented in MATLAB and its GNU clone Octave. The graph traversal algorithm, many geometric relations, basic shapes such as 3D boxes, and other objects such as trucks were tested. The current implementation is still in a prototype stage and we tested it only on a limited set of images.

Several issues arise in implementing the algorithm. Among them:

**Representation of nodes and links.** Most modern programming languages such as C, Fortran, MATLAB, have a data structure called a “structure array”. We implement our graph representation as such an array. The structure contains fields that can be accessed by their names and these can contain quite arbitrary content. In a typical example, the fields contain employee name, address, phone number, etc. The structures are indexed as an array to account for different employees. In our implementation each node is represented by a structure having fields such as:

- **Type**: truck
- **Instance**: 1
- **Parts**: cabin, trunk-a, trunk-b, wheels
- **Groups**: convoy
- **Higher LoA**: vehicle
- **Lower LoA**: truck1, truck2
- **Origin**: x,y,z
- **Axes**: ax1, ax2, ax3
- **Elasticity k**
- **Part(i) origin**: x,y,z
- **Part(i) axes**: ax1, ax2, ax3
- **Part(i) elasticity**: k(i)
- **Midx**: cabin, trunk-a: truck1
- **Relations**: (“size-ratio”, cab, trunk-a, 2, 0.3)
- **Relations**: (“distance-ratio”, cab, trunk-a, 1.5, 0.3)

The “midx” field lists hypotheses of possible groups, indexed by two parts. These hypotheses are screened using the relations between these parts listed in the “relations” field. These two parts are sufficient to generate a hypothesized coordinate transformation between the model and the image. We can then perform a verification by transforming the model onto the image and check these and other parts.
The data in the “relations” field is inspired by the syntax of Lisp. Each relation is a list whose first element is a name of a relation function, in this example “size-ratio”. Given the hypothesis “truck1”, this function finds the ratio of sizes of the “cabin” and the variant “trunk-a” of the trunk. A hypothesis “truck1” proceeds to verification when this relation is satisfied. For this relation to be satisfied, the function “size-ratio” has to return the value of “2” with tolerance 0.3. This function is one of general relation functions that can be checked. They can be geometric such as “ratio”, “pose” (checking relative poses including parallelism), or they can be topological relations such as “touch” or “inside”. These generic functions can be used for any objects.

**Low level features.** Features such as edges should be integral parts of the hierarchies. An edge cannot be detected reliably on its own but as a part of a bigger object. An edge should be strengthened if it is a part of (e.g.) a line segment and weakened otherwise, and this can be handled naturally by our probability propagation algorithm. However this is not fully implemented yet and for the current examples we have used standard edge detectors.

**Symmetric objects** have multiple representations. A line segment does not have a direction, but it is hard to represent it analytically without a direction, thus it has two representations corresponding to the two possible directions. Similarly, a box has 48 representations. This complicates the testing of the hypotheses as we have to test 48 boxes instead of one. We have found a way to avoid this by using a testing method that is invariant to these different representations.

**Projection from 3D to 2D.** Although a box is made up of rectangles in 3D, these rectangles are projected onto 2D as parallelograms (assuming affine projection). The hypothesis generation has to be adjusted accordingly. Some relations are invariant to this projection and can be used to screen hypotheses. In [11] such invariant relations were derived for a cloud of points but they do not take the structure of the object into account. In [10] invariants of curves were used based on derivatives. In the current implementation we use simpler invariant properties such as parallelism and the ratios of parallel line segments. For instance, given parallel lines in 2D, we can hypothesize that they are parallel in 3D.
In the following example we have tested the viewpoint invariance of our algorithm using a 3D truck projected from different points of view. Figure 8 shows an edge map generated by a conventional edge detector and Figure 9 shows line segments based on these edges. These were fed into our algorithm. Figure 10 shows the resulting boxes and a truck recognized by our algorithm as “truck1” expressed in the model graph. Figure 11 shows the result of our algorithm applied to the same truck seen from a different viewpoint. We have recognized it as the same truck. This is because it has the same structure and invariant relations in both images. That is, the ratios of lengths of parallel sides of various rectangles, as well as the ratios of sides of rectangles to distances in parallel directions, are the same in both views. There is no 2D geometric transformation between two 2D images projected from 3D, so they cannot be matched by a template-based method even if it tries to account for transformations.

10. Conclusion

We have presented an object recognition system based on the structure and geometry of objects, using a machine-learnable model graph. The system is more versatile than previous ones by having two distinct hierarchies of models, both of which can be built by the system: parts and abstraction. Although the concepts of abstraction and semantics seem human, we define them in a computational way that has no reliance on human perception or language. This makes it possible to build a fully automated learning and recognition system. This is done by an algorithm that moves in both hierarchies at the same time, combining both bottom-up and top-down strategies. This reduces the dimensionality of both the learning and recognition processes, avoiding the need for “big data” training.

Because the system classifies specific objects into generic ones based on intrinsic structure rather than pixels, the classification is much more robust than current ML methods with respect to small variations in the object. A stop sign will not be misclassified just because it has a sticker on it. In that our system is similar to human recognition and therefore the classification is transparent and understandable by humans, unlike current ML classifications. It is also robust with respect to various external variations such as viewpoint or illumination changes.

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