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PRACTICAL APPLICATIONS OF FUZZY SIGNATURES: A REVIEW

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Abstract
Fuzzy signatures are hierarchical fuzzy data structures, introduced by Vámos et al., that represent complex, uncertain information as a tree of interrelated fuzzy sets instead of a single flat variable. This article reviews six active domains where fuzzy signatures have been applied in practice: structural and civil engineering assessment, robotics, medical diagnosis, document and text analysis, engineering and facility decision support, as well as human resources and organizational behavior analytics. Based on a focused reading of recent literature rather than an exhaustive systematic search, this article describes how each domain builds its hierarchy and highlights open challenges, including how to choose or learn aggregation weights, how to handle hierarchies that adapt to new data, and the lack of shared benchmarks and general-purpose tools. This review aims to give practitioners and researchers a practical overview of where and how fuzzy signatures are used today.

1 Introduction

A fuzzy signature stores complex, uncertain information as a tree of connected fuzzy sets instead of a single flat variable. Each branch of the tree describes one attribute of the object, and any branch can split into smaller sub-branches when more detail is needed. Consequently, the same structure can hold something as simple as one measurement, or as rich as a multi-level assessment of a whole system. Vámos et al. [1] introduced the idea as a generalization of earlier vector-valued fuzzy sets [2], aiming to model real-world objects whose attributes are naturally uncertain and organized in levels rather than laid out in a single list. The structure handles noise, missing values, and uneven detail well, which may explain why researchers in many different fields have adopted it.

Those fields have little in common at first sight: civil engineering, robotics, medical diagnosis, text analysis, facility management, and organizational behavior research. Work on fuzzy signatures is spread across their journals and conferences, so it is not easy to get a picture of the field as a whole. This review aims to provide such an overview. It collects a focused set of recent, representative examples from each of the six domains listed above. It is not a complete systematic survey; the goal is a concise overview of the current state of practice.

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The paper is organized as follows. Section 2 explains what a fuzzy signature is and how values are combined across its hierarchy. Section 3 walks through the six application domains one by one. Section 4 compares them and points out the challenges they share. Section 5 closes with a short summary and some ideas for future work.

2 Background and core concepts

This section defines the fuzzy signature concept used throughout the review and explains how information is combined across its hierarchy.

2.1 What is a fuzzy signature?

A fuzzy signature is a hierarchical data structure that puts several fuzzy sets together to describe something too complex for a single fuzzy variable [1]. Structurally, it is a tree: each branch holds either a simple fuzzy value or another, smaller fuzzy signature, and this nesting can go as deep as the problem needs, as Figure 1 shows. As a result, one signature can hold partial, uncertain, and unevenly detailed information about the same object side by side. A flat list of variables cannot do that easily.

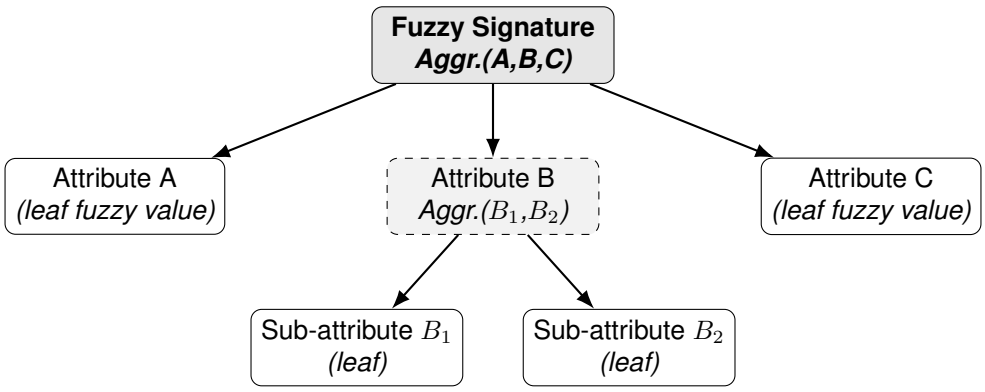

Figure 1. The hierarchical structure of a fuzzy signature. The root describes a complex object through several attributes; each node can be either a simple fuzzy value (a leaf) or another, smaller fuzzy signature (a nested branch, shown dashed), which can itself expand into further leaves or branches.

In more formal terms, a fuzzy signature maps an object's universe of discourse to a vector of components. Each component is either a leaf, that is, a single fuzzy value for one attribute, or a branch, that is, another, smaller fuzzy signature with components of its own. The definition is recursive, and that is exactly what makes the nesting in Figure 1 possible: Attribute B is not a fixed list of numbers but a complete fuzzy signature in its own right, and it may contain further branches or leaves. Nothing in the definition fixes how many components a signature has or how deep it nests. Because of this, the same formalism covers a shallow two-level assessment as well as a deep hierarchy with dozens of sub-branches.

An example illustrates this. Consider the description of the condition of a wall in a building. A flat approach would need one variable per property, and structural and material information would sit awkwardly at the same level. A fuzzy signature instead groups related properties. One branch might hold structural attributes such as crack width and load-bearing capacity, while a separate branch holds material attributes such as moisture content and surface deterioration. Either branch can grow further sub-branches if more detail becomes available. Section 3.1 returns to a similar example when it reviews a real fuzzy signature model for masonry assessment.

2.2 Aggregating information across the hierarchy

A fuzzy signature is only useful once the values held in its lower branches can be combined into a value for the branch above them, and eventually into a single judgment at the root. This combination step is handled by an aggregation operator: a function that takes several fuzzy values, one per child branch, and returns one fuzzy value for the parent. Common choices include the minimum, the maximum, the arithmetic mean, the algebraic product, and weighted variants of these.

The choice of aggregation operator is not a minor implementation detail: it can change the practical outcome substantially. Karadeniz et al. [3] compared four aggregation operators (minimum, maximum, algebraic product, and arithmetic mean) for combining sensor readings in a robot path-planning task, and found that the algebraic product produced paths up to 35.3% shorter and cut execution time by up to 52.5% compared with the maximum operator. A similarly strong sensitivity to the aggregation choice shows up in other domains, as discussed in Section 3. Because no single aggregation operator works best for every hierarchy, choosing or learning the right one for a given problem remains an active design question, and one of the recurring challenges discussed in Section 4.

3 Practical application domains

Fuzzy signatures have been applied in a wide range of real-world domains. This section reviews six of the most active ones, the way each builds its hierarchy, and what has been reported about the results. Figure 2 gives an overview of the six domains covered below.

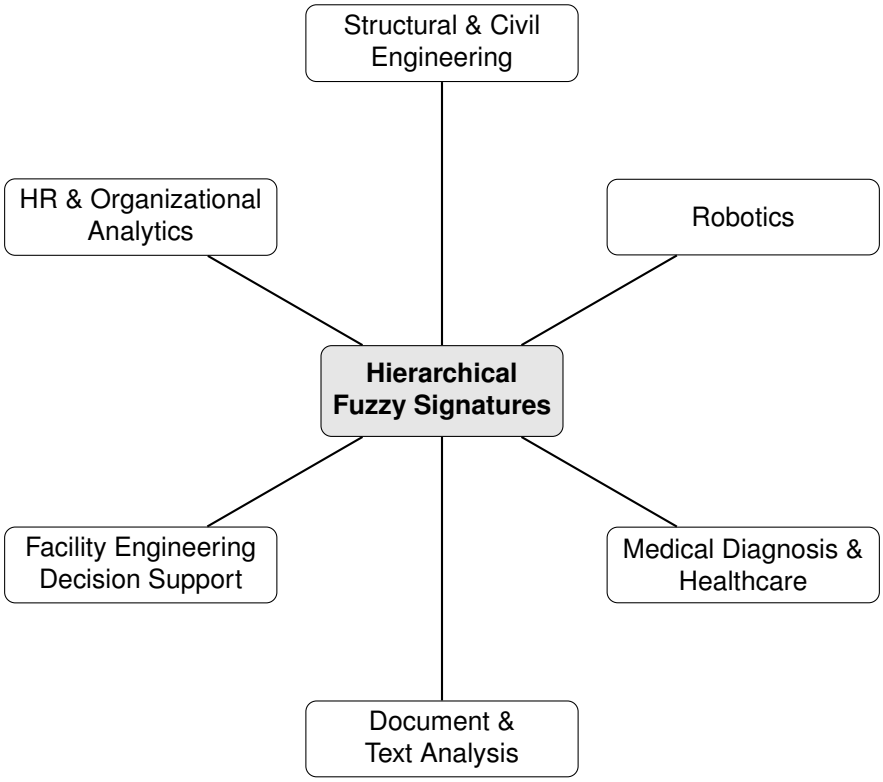

Figure 2. The six practical application domains reviewed in this section, each built on the hierarchical fuzzy signature structure introduced in Section 2.

3.1 Structural and civil engineering

Assessing the condition of an aging structure usually means combining two very different kinds of evidence: numeric measurements from non-destructive testing equipment, and a qualitative judgment from an experienced inspector who has looked at the structure in person. Kaszás et al. [4] built a hierarchical fuzzy signature model that does exactly this for masonry structures, combining

non-destructive measurement data with expert visual inspection into a single, structured assessment of whether a wall or building is loadable, repairable, or should be demolished. For each masonry component, the signature branches into a Visual Inspection subsignature and an Instrumental Test subsignature, with the latter further split into Brick, Mortar, and Masonry sub-branches, so that subjective inspector judgments and objective measured parameters are kept in separate branches until the aggregation step combines them, rather than being forced into a common format from the start.

For the aggregation operator itself, Kaszás et al. chose the *weighted geometric mean (WGM)* at every internal node of the signature. This choice was not arbitrary: the Eurocode 6 formula for masonry compressive strength combines brick and mortar strength through a product of terms raised to fixed exponents, and the WGM mirrors that same multiplicative logic, so the fuzzy aggregation stays consistent with the standard engineering formula it is meant to complement rather than replace. In each WGM operation the weights, expressed as the exponents of the leaf and branch values, reflect how important the corresponding measurement or judgment is to the parent node, and a missing or unreliable reading is handled cleanly by fixing its membership value to 1 and its weight to 0, so it drops out of the aggregation without disturbing the rest of the weights, which must still sum to 1.

Because there is no established table of correct weights for this kind of hierarchy, the authors treated the weights as free parameters and optimized them against real data: using 114 parameter combinations from destructive tests on existing masonry, they compared the Monte Carlo method, a genetic algorithm, and particle swarm optimization to find the WGM exponents that made the signature's evaluation match the destructive-test outcome as closely as possible. All three optimizers found the extreme values of the objective function with relatively high confidence. The authors also examined how the distribution of the resulting weights affects the consistency of the evaluation: symmetric weighting simplifies the aggregation, while asymmetric weighting allows local structural irregularities to be highlighted. Beyond a single wall, the same WGM-based hierarchy scales up: several per-wall signatures can be combined into one signature for an entire building, whose root aggregation yields a five-way linguistic verdict, loadable, usable, partially repairable, repairable, or to demolish, which would give engineers a single, traceable recommendation built from a mix of hard measurements and expert opinion. The authors note, however, that this assembled building-level case has so far been tested only theoretically, because validation measurements were available only for single masonry signatures.

3.2 Robotics

Robotics is an established application area for fuzzy signatures, and it remains active today. Karadeniz et al. used a fuzzy signature to represent a mobile robot's local environment from multiple sensor readings, and applied it to path planning: as described in Section 2.2, the choice of aggregation operator had a strong effect, with the algebraic product giving the shortest paths and the fastest planning times [3].

Earlier work by Ballagi et al. already showed two other robotics uses of the same structure [5]. First, a fuzzy-signature-based motion control system represented a robot's entire state space as a fuzzy signature, giving a lateral drift control method in which the fuzzy signature representation adds flexibility, adaptability, and learning ability to the system. Second, a fuzzy communication scheme let cooperating mobile robots build a shared "codebook" out of fuzzy signatures, so that robots working together could exchange compact, structured messages about what they were sensing. Together, these examples show fuzzy signatures being useful both inside a single robot's perception and planning pipeline, and between robots that need to coordinate.

Fuzzy signatures are not the only fuzzy-based structure used to steer robots. Vaščák et al. combined fuzzy cognitive maps with an Internet-of-Things architecture to give mobile robots a reactive navigation capability, representing a robot's surroundings as a network of fuzzy causal relationships rather than a nested attribute hierarchy [6]. On the control side, Škrjanc et al. proposed a model-reference fuzzy adaptive control framework for nonlinear systems, an approach relevant to robot control that complements the perception- and planning-oriented fuzzy signature work described

above [7]. Neither approach uses the hierarchical fuzzy signature structure defined in Section 2.1, but both illustrate how widely fuzzy methods in general have been adopted in robotics.

3.3 Medical diagnosis and healthcare

Hossain et al. [8] applied aggregated fuzzy signature structures to a five-class medical diagnosis problem, classifying patients as having SARS, a normal presentation, high blood pressure, pneumonia, or COVID based on their symptom and test attributes. The signature groups each patient's readings into low-level attribute branches, such as several individual temperature readings and separate systolic and diastolic blood-pressure readings, which are aggregated upward into intermediate features before those features are combined once more into the final class score at the root, giving the signature three levels between raw symptom readings and diagnosis.

Rather than committing to one aggregation operator, Hossain et al. treated the operator itself as an experimental variable at every level of this hierarchy, cycling through the *minimum*, the *maximum*, the *arithmetic mean*, and an additional *mean-max hybrid operator* that averages the arithmetic mean and the maximum of the children's values; the authors' implementation is publicly available [9]. Trying every assignment of these four operators to the three aggregation levels produced 64 (4^3) distinct fuzzy signature configurations over the same underlying data. Some of these combinations reached 100% accuracy on their dataset, while for a few others the model did not work well. When compared against a K-Nearest Neighbor classifier (up to about 98% precision) and a Support Vector Machine (up to about 87% accuracy) on the same data, the best fuzzy signature configurations were competitive with both, while keeping the hierarchical structure of the diagnosis interpretable.

Fuzzy logic has also reached other medical tasks beyond diagnosis. Precup et al. designed a fuzzy control solution for telesurgical applications that alleviates the effects of large latencies in remote surgical robotics, replacing the outer-loop PID controller of a cascade control structure with Takagi–Sugeno PID-fuzzy controllers [10], a control-focused complement to the diagnosis-focused fuzzy signature work described above.

3.4 Document and text analysis

Text has a natural hierarchy of its own: documents are made of sentences, sentences are made of words, and words can be grouped into types such as names, places, or dates. Manna et al. [2] built a hierarchical document signature that follows this structure directly. Their signature has four levels, running from the whole document down to sentences, then to attributes (name, place, term, and time), and finally to individual words. The raw input at the bottom consists of word occurrence counts, normalized by sentence and word length. From these counts, a similarity score between any two sentences in a document is built up one level at a time.

At the word level, the authors tried several operators for turning two words' normalized frequencies into a similarity value: the *minimum*, the *maximum*, the *arithmetic mean*, and a *fuzzy Jaccard coefficient (FJC)*, which is the ratio of the minimum of the two frequencies to their maximum. The FJC performed best and matched human judgments of sentence similarity most closely. The minimum gave identical values to several sentence pairs, and the maximum in one case ranked a pair sharing only a single word above pairs that shared several. One level up, each word similarity is multiplied by an attribute weight equal to the inverse of the number of words of that attribute (name, place, term, or time) in the document, and the weighted similarities of the words common to the two sentences are then averaged with the *arithmetic mean*; the authors also compared the maximum and minimum at this level and chose the mean. Finally, at the sentence level, the four attribute-level scores are merged with the *maximum* operator into a single similarity value for the sentence pair. On the sample data, the maximum, mean, and minimum produced the same ranking of sentence pairs at this level, and the authors used the maximum.

The authors tested the method on a small example and on a set of real news documents about a plane crash. In both cases it placed clearly related sentence pairs above less related ones, in line with human intuition.

3.5 Facility and engineering decision support

Buildings and other engineering facilities can be assessed against many criteria at once, e.g., structural condition, energy efficiency, safety compliance, and more, often with some criteria only partially known. Bukovics et al. [11] built a decision support system for buildings. The system, called the Complex Building's Decision Support System based on Fuzzy Signatures (CBDF), uses a fuzzy signature that combines this range of inspection criteria into one consistent, explainable recommendation for renovation or investment decisions. The system tailors its fuzzy signature to the building under review and the stated objective, whether that is assessing general load-bearing capacity, optimizing renovation spending, checking for urgent safety risks, or evaluating demolition, and it draws on a knowledge base of boundary criteria compiled from expert practice and the specialized literature, targeted at the historic residential buildings common in inner-city Budapest.

As a typical aggregation operator for the branches of the signature, Bukovics et al. present the *Weighted Relevance Aggregation Operator (WRAO)*, a weighted power mean that raises each leaf's value, scaled by its weight, to a power p, averages the results, and takes the p-th root, so that it behaves more like a weighted arithmetic mean or more like a weighted maximum or minimum depending on p. Each branch of a building's signature can have its own aggregation operator. In the paper's example of the stone plates of side corridors, separate operators aggregate the crack, damage, and stability inspections of each plate, and a further operator combines these inspections. This operator uses *state-dependent dynamic weighting*: the crack, damage, and stability scores are combined with base weights (0.6, 0.2, and 0.2) and multiplied by modifying factors that depend on the situation, such as vibration, load-bearing surplus, and strutting. For example, the authors note that in a building with a metro line running underneath, vibration makes corrosion a comparatively bigger threat than in a building without that exposure, so the assessment adapts to the context rather than applying fixed weights.

A key design goal was tolerance for missing or uncertain input: rather than forcing an all-or-nothing evaluation when some criteria cannot be measured, the fuzzy signature produces a graded assessment from whatever evidence is available, and a dedicated credibility factor separately tracks how much missing data or shallow (rapid rather than detailed) inspection has reduced confidence in that assessment. This combination is aimed at giving professionals a more objective and repeatable basis for renovation and investment decisions that were previously made largely by individual judgment.

3.6 Human resources and organizational analytics

Employee surveys are a natural fit for fuzzy signatures because a single questionnaire response is rarely a single precise value: it reflects a mix of related but distinct impressions, expressed with varying degrees of confidence. Kóczy et al. [12] built a combined statistical and fuzzy-signature model to analyze questionnaires about organizational citizenship behavior (OCB) and counterproductive work behavior (CWB). The same model is described in detail in an open-access companion paper by the same research group [13]. Each respondent's fourteen Likert-scale answers were normalized to the unit interval and organized into two branches, one for the positive OCB items and one for the negative CWB items. Because a negative attitude cannot be combined directly with a positive one, the aggregated CWB value was complemented (subtracted from 1) before entering the root, so that both branches pointed in the same, increasing direction.

For the aggregation operator, the OCB branch relies mainly on the *weighted arithmetic mean*, with weights set by management-expert judgment to reflect how much each underlying item matters. For instance, the Altruism node combines two items as $0.75Q_{01}+0.25Q_{02}$ because experts judged the first item roughly three times more important in daily work, while other nodes, such as Sportsmanship, Civic virtue, and Compliance, were each assumed to combine two equally important sub-items and so received an internal $0.5/0.5$ split, and the five OCB sub-nodes feeding the root were each weighted $1/5$. The CWB branch uses the *maximum operator*, on the reasoning that a respondent's single worst counterproductive tendency should dominate the combined score rather than being diluted by

an average. At the root, the Citizenship Behavior score and the complemented Counterproductive Behavior score are combined once more with a weighted arithmetic mean, weighted $2/3$ and $1/3$ respectively, reflecting the assumption that positive engagement carries roughly twice the influence of the negative factor.

Beyond this expert-defined hierarchy, Kóczy et al. also built an alternative version of the same signature using factor analysis to regroup the fourteen items statistically rather than by expert judgment, arriving at similarly weighted-arithmetic-mean aggregations but with different groupings and weights. In a further variant, one item (Q12) that loaded on two different factors was given a fuzzy, partial membership in both branches, rather than being forced into a single node [13]. The expert-assigned weights were further tuned to maximize the multiple correlation between the resulting engagement score and independently collected job-satisfaction items, reaching a correlation of 0.685. By representing each respondent's set of related answers as a fuzzy signature rather than reducing them immediately to a single numeric score, the model preserved more of the original nuance in the data, and supported a more detailed analysis than a purely statistical approach would have allowed.

4 Comparative analysis and challenges

This section compares the six application domains and identifies the challenges they share.

4.1 Comparing the domains

Table 1 summarizes how each application builds its fuzzy signature, which aggregation approach it uses, and what has been reported about the outcome.

Table 1. Comparison of fuzzy signature application domains

Domain	Typical hierarchy	Aggregation approach	Reported outcome
Structural / civil engineering	Measurement and expert-inspection branches	Weighted geometric mean; weights optimized against destructive-test data	Single loadable / repairable / demolish judgment from mixed numeric and qualitative data [4]
Robotics	Two-level, quadtree-based spatial hierarchy of sensed obstacle points	Min, max, algebraic product, mean (compared directly)	Best operator gave up to 35.3% shorter paths and 52.5% faster planning [3]; adaptable motion control and inter-robot codebooks [5]
Medical diagnosis	Symptom / test attribute branches per class	Many aggregation combinations compared	Up to 100% accuracy for the best combinations; a few combinations performed poorly [8]
Document / text analysis	Document $\rightarrow$ sentence $\rightarrow$ attribute $\rightarrow$ word	Mean at attribute level, max at sentence level	Sentence-pair similarity rankings consistent with human judgment [2]
Facility / engineering decision support	Inspection-criteria branches, some incomplete	Branch-specific weighted operators (e.g., WRAO) with state-dependent weights	Consistent, explainable renovation and investment decisions [11]
HR / organizational analytics	Questionnaire-item branches per respondent	Weighted arithmetic mean (OCB), maximum (CWB)	Preserved nuance in imprecise survey responses [12] [13]

A few patterns stand out. First, every domain uses the hierarchy to combine data sources that would otherwise be difficult to merge: numbers with expert opinions, sensor readings with each other, symptoms with test results, words with sentences, or individual questionnaire items with each other. Second, in each domain that directly compared aggregation strategies, the choice of operator

changed the outcome by a wide margin, echoing the point made in Section 2.2. Third, the two engineering applications explicitly value the ability to handle missing or unreliable data, whether that is an unmeasured or unreliable reading in a masonry assessment or an incomplete building inspection.

4.2 Challenges

Despite these results, several problems recur across domains.

Choosing or learning aggregation weights. As Sections 2.2 and 3 both show, results are highly sensitive to the aggregation operator and weights chosen at each level of the hierarchy. There is no general theory yet for picking the right operator automatically for a new problem; half of the studies reviewed here (the robotics, medical and text-analysis studies) selected theirs by trying several options and comparing the results empirically, while the others relied on engineering rationale or expert judgment.

Designing the hierarchy itself. Unlike a flat feature vector, building the tree, deciding how many levels it needs and which attributes belong where, is a manual step guided by domain expertise. This makes fuzzy signature models effective once built, but slow to set up for a new problem, and hard to automate.

Comparing across studies. Because each domain defines its own hierarchy, data, and evaluation metric, there is no shared benchmark that would let researchers compare aggregation strategies, or fuzzy signatures against other methods, on equal footing across domains.

Tooling. Most of the implementations described in Section 3 are research code, custom-built for a single study. No widely used, general-purpose software library for building and aggregating fuzzy signatures appears to exist yet, which raises the barrier to entry for new applications.

4.3 Open research directions

Several directions look promising for closing these gaps. The strong dependence of accuracy on the aggregation combination that Hossain et al. reported [8] points to the first one: learning aggregation weights from data instead of setting them by hand, perhaps by pairing fuzzy signatures with machine learning methods. A second direction follows from the path-planning results of Karadeniz et al. [3]. Since the choice of operator mattered so much there, careful studies of when each operator works best, across domains rather than within a single one, would help practitioners make a good choice from the start. Shared benchmark datasets and a common software library would also make it much easier to compare results across the structural, robotics, medical, textual, facility, and organizational domains reviewed here. Finally, almost every hierarchy described in Section 3 is built once and then stays fixed. Hierarchies that can grow or adapt as new data arrive remain largely unexplored and merit further research.

5 Conclusions

When fuzzy signatures appeared in 1999, they were a fairly abstract generalization of fuzzy sets, meant to represent complex objects as a hierarchy rather than a flat list of variables [1]. Today the idea is used in practice. As this review has shown, it now reaches into structural and civil engineering, robotics, medical diagnosis, document and text analysis, facility decision support, and organizational behavior research.

One thread runs through all six domains: the ability to merge mixed, partial, and layered information into a single, consistent judgment. Sometimes that means combining instrument readings with expert opinion. In other cases it means fusing several sensors, weighing symptoms together, rolling word-level data up into sentence similarity, coping with an incomplete building inspection, or keeping the fine detail in survey answers.

The difficulties repeat across domains as well. Results depend strongly on the choice of aggregation operator, building the hierarchy is still manual work for domain experts, and there is little shared tooling or benchmarking. Progress on these points, above all learning aggregation weights from data and creating common tools and benchmarks, would make fuzzy signatures easier to adopt

for new problems and easier to compare fairly with other methods. Six very different fields have already put the same basic structure to work, and further application areas are likely to follow.

References

[1] T. Vámos, Gy. Bíró, and L. T. Kóczy, "Fuzzy signatures," in *Proc. EUROFUSE-SIC 99: 4th Meeting of the EURO Working Group on Fuzzy Sets and 2nd Int. Conf. on Soft and Intelligent Computing*, B. De Baets, J. Fodor, and L. T. Kóczy, Eds. Budapest, Hungary, 1999, pp. 210–217.

[2] S. Manna, B. S. U. Mendis, and T. Gedeon, "Hierarchical document signature: A specialized application of fuzzy signature for document computing," in *Proc. 2009 IEEE Int. Conf. Fuzzy Syst. (FUZZ-IEEE)*, Jeju Island, South Korea, 2009, pp. 1083–1088. DOI: 10.1109/FUZZY.2009.5277054.

[3] A. M. Karadeniz, C. Hajdu, Á. Ballagi, and L. T. Kóczy, "Evaluating the impact of aggregation operators on fuzzy signatures for robot path planning," *Sensors*, vol. 25, no. 23, art. no. 7342, 2025. DOI: 10.3390/s25237342.

[4] A. Kaszás, V. O. Pomezanski, and L. T. Kóczy, "Hierarchical construction of fuzzy signature models for non-destructive assessment of masonry strength," *Symmetry*, vol. 17, no. 10, art. no. 1764, 2025. DOI: 10.3390/sym17101764.

[5] Á. Ballagi, L. T. Kóczy, and T. D. Gedeon, "Fuzzy communication and motion control by fuzzy signatures in intelligent mobile robots," in *Aspects of Soft Computing, Intelligent Robotics and Control*, Studies in Computational Intelligence, vol. 241, Springer, Berlin, Heidelberg, 2009, pp. 147–164. DOI: 10.1007/978-3-642-03633-0_9.

[6] J. Vaščák, L. Pomsár, P. Papcun, E. Kajáti, and I. Zolotová, "Means of IoT and fuzzy cognitive maps in reactive navigation of ubiquitous robots," *Electronics*, vol. 10, no. 7, art. no. 809, 2021. DOI: 10.3390/electronics10070809.

[7] I. Škrjanc, S. Blažič, and D. Matko, "Model-reference fuzzy adaptive control as a framework for nonlinear system control," *Journal of Intelligent and Robotic Systems*, vol. 36, no. 3, pp. 331–347, 2003. DOI: 10.1023/A:1023089005353.

[8] M. Z. Hossain, Z. Jin, T. Gedeon, A. Biswas, R. Tabassum, F. H. Shubho, and S. Rahman, "Aggregated fuzzy signature structures for multi-class medical diagnosis," in *Neural Information Processing (ICONIP 2024)*, Communications in Computer and Information Science, vol. 2286, Springer, Singapore, 2025, pp. 16–30. DOI: 10.1007/978-981-96-6960-8_2.

[9] M. Z. Hossain *et al.*, "Fuzzy-for-Medical-Diagnosis: Code for aggregated fuzzy signature structures for multi-class medical diagnosis," GitHub repository. [Online]. Available: https://github.com/md-zakir-hossain/Fuzzy-for-Medical-Diagnosis

[10] R.-E. Precup, T. Haidegger, S. Preitl, Z. Benyó, A. S. Paul, and L. Kovács, "Fuzzy control solution for telesurgical applications," *Applied and Computational Mathematics*, vol. 11, no. 3, pp. 378–397, Sep. 2012. [Online]. Available: http://www.acmij.az/view.php?lang=az&menu=cjournal&id=289

[11] Á. Bukovics, F. Lilik, and L. T. Kóczy, "Complex building's decision support method based on fuzzy signatures," *Buildings*, vol. 14, no. 6, art. no. 1630, 2024. DOI: 10.3390/buildings14061630.

[12] L. T. Kóczy, D. Susnienė, O. Purvinis, and D. Žostautienė, "Analyzing employee behavior related questionnaires by combined fuzzy signature model," *Fuzzy Sets and Systems*, vol. 395, pp. 254–272, 2020. DOI: 10.1016/j.fss.2020.04.018.

[13] D. Susnienė, O. Purvinis, D. Žostautienė, and L. T. Kóczy, "Modelling OCB and CWB by combined fuzzy signature model," *Economic Research–Ekonomska Istraživanja*, vol. 34, no. 1, pp. 1546–1565, 2021. DOI: 10.1080/1331677X.2020.1844581.