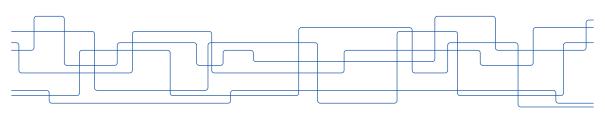


"Fuzzy morphisms between graphs" (Perchant & Bloch, 2002) and "Fuzzy graphs" (Rosenfeld, 1975)

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Disposition

- 1. Primer Fuzzy Graph Theory
- 2. What? Fuzzy Graph Morphisms
- 3. Why? Applications of Fuzzy Graph Morphisms
- 4. Conclusions
- 5. Demo!

A Primer to Fuzzy Graph Theory

- 1. Fuzzy Logic
- 2. Fuzzy Graph Theory

Fuzzy Logic

Definitions from "Fuzzy graphs" (Rosenfeld, 1975).

Fuzzy subsets

Definition: A *fuzzy subset* of a set S is a mapping $\sigma: S \to [0,1]$ which assigns each element $x \in S$ a degree of membership $0 \le \sigma(x) \le 1$.

Examples:

- ▶ Deina \in old with $\sigma(Deina) = 0.3$
 - ▶ The element *Deina* (woman at age 34) is a member of the set *old* to a degree of 0.3
- ► Fourfoutos \in old with σ (Fourfoutos) = 0.5
 - ▶ The element *Foufoutos* (man at age 45) is a member of the set *old* to a degree of 0.5
- ► $Tade \in old$ with $\sigma(Tade) = 0.1$
 - ▶ The element *Tade* (boy at age 6) is a member of the set *old* to a degree of 0.1

Fuzzy Logic

Fuzzy relations

Definition: A fuzzy relation on a set S is a mapping $\mu: S \times S \to [0,1]$ which assigns each ordered pair $(x,y) \in S \times S$ a degree of membership $0 \le \mu(x,y) \le 1$. In other words, a fuzzy relation on S is a fuzzy subset of $S \times S$.

Examples:

- ▶ (Deina, Tade) ∈ mothers with μ (Deina, Tade) = 1.0, where mothers : person × person
 - ► The ordered pair (*Deina*, *Tade*) is a (*mother*, *child*)-relation on the set *person* to a degree of 1.0
- ► (Foufoutos, Tade) ∈ fathers with μ (Foufoutos, Tade) = 0.5, where fathers : person × person
 - ► The ordered pair (*Foufoutos*, *Tade*) is a (*father*, *child*)-relation on the set *person* to a degree of 0.5

Fuzzy Logic

Definitions from "Fuzzy morphisms between graphs" (Perchant & Bloch, 2002).

Fuzzy relation on $\sigma_1 \times \sigma_2$

Let $\sigma_1: S_1 \to [0,1]$ and $\sigma_2: S_2 \to [0,1]$ be fuzzy subsets of S_1 and S_2 , respectively.

Definition: The function $\mu: S_1 \times S_2 \to [0,1]$ is a *fuzzy relation* on $\sigma_1 \times \sigma_2$ iff:

$$\forall (x, y) \in S_1 \times S_2 : \mu(x, y) \le \sigma(x) \land \sigma(y)$$
 (1)

Note: \land denotes *minimum* (and \lor denotes *maximum*).

Intuition: A fuzzy relation cannot be "stronger" than either of its elements.

Fuzzy Graph Theory

Fuzzy graph

Definition: A fuzzy graph $F = (\sigma, \mu)$ is a pair of functions $\sigma : S \to [0, 1]$ and $\mu : S \times S \to [0, 1]$ which satisfy equation 1 (of previous slide).

Intuition: For a given graph G(V, E), a fuzzy graph $F(\sigma, \mu)$ has a fuzzy subset σ of V and a fuzzy subset μ of $V \times V$. Since equation 1 (of previous slide) is satisfied, a "fuzzy edge" cannot be stronger than either of its "fuzzy endpoint vertices".

Fuzzy Graph Theory

Max-min composition

Let μ_1 and μ_2 be two fuzzy relations on $\sigma_1 \times \sigma_2$ and $\sigma_2 \times \sigma_3$, respectively.

Definition A max-min composition of μ_1 and μ_2 , denoted by $\mu_1 \circ \mu_2$, is defined as follows.

$$\forall (u_1, u_3) \in S_1 \times S_3, (u_1 \circ u_2)(u_1, u_3)$$

$$= \sup_{u_2 \in S_2} \{ \mu_1(u_1, u_2) \wedge \mu_2(u_2, u_3) \}$$
(2)

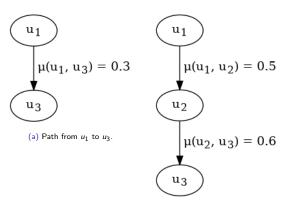
Note: sup (supremum) denotes *least upper bound* (and \land denotes *minimum*).

Intuition: select the best "middle" vertex u_2 such that a path from u_1 to u_2 and u_2 to u_3 has the highest "quality", as measured by the lowest edge weight $\mu(x,y)$ along that path.

Fuzzy Graph Theory

Max-min composition

Going through u_2 improves "quality" of path from $\mu(u_1, u_3) = 0.3$ to $(u_1 \circ u_2)(u_1, u_3) = 0.5$.



(b) Path from u_1 through u_2 to u_3 .

Figure: Find better "quality" path using max-min composition.

What?

(Sub)graph isomorphism requires a *bijective* mapping to match vertices and edges of two graphs. In other words, there may exist no missing or additional vertices or edges.

The real world is not ideal, as such we are often interested in *inexact* graph matches.

Fuzzy graph morphisms are used to formalize inexact graph matches.

Fuzzy Graph Morphisms

Fuzzy Graph Morphisms

Definition: A fuzzy morphism $(\rho_{\sigma}, \rho_{\mu})$ between graphs G_1 and G_2 is a pair of mappings $\rho_{\sigma}: N_1 \times N_2 \to [0,1]$ and $\rho_{\mu}: N_1 \times N_2 \times N_1 \times N_2 \to [0,1]$ which satisfy:

$$\forall (u_1, v_1) \in N_1 \times N_1, \forall (u_2, v_2) \in N_2 \times N_2 :
\rho_{\mu}(u_1, u_2, v_1, v_2) \le \rho_{\sigma}(u_1, u_2) \wedge \rho_{\sigma}(v_1, v_2)$$
(3)

Corollary: A fuzzy morphism $(\rho_{\sigma}, \rho_{\mu})$ is a fuzzy graph, and equation 3 is analogous to equation 1.

The mapping ρ_{σ} is called a *vertex morphism* and ρ_{μ} a *edge morphism*.

Fuzzy Graph Morphisms

Example:

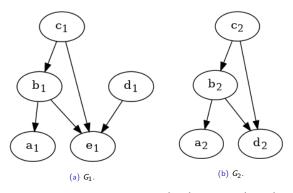


Figure: Example graphs G_1 (left) and G_2 (right).

Internal Representation of Fuzzy Graph Morphisms

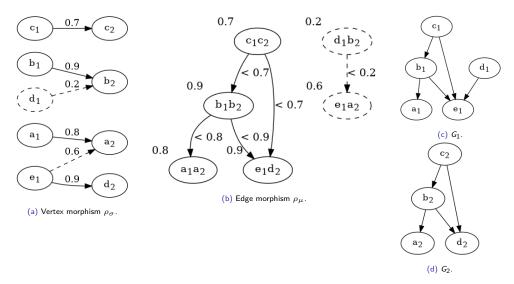


Figure: Internal representation of fuzzy graph morphism $\rho(\sigma, \mu)$.

External Representation of Fuzzy Graph Morphisms

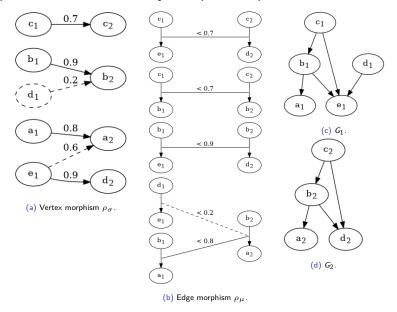


Figure: External representation of fuzzy graph morphism $\rho(\sigma, \mu)$.

Why?

Applications of Fuzzy Graph Morphisms

- ► Binary analysis
 - ► Function identification by matching fuzzy graph morphisms of callgraphs, control flow and data flow graphs.
- Pattern recognition
- Image analysis
 - Fuzzy graph morphisms of regions (vertices) and relation between regions (edges).
- Recognition of brain structures
 - Fuzzy graph morphisms of neurons (vertices) and synapses (edges)

Conclusions

- 1. Significance of papers
- 2. Relation to other research

Significance of papers

Rosenfeld was among the first to formalized fuzzy graph theory in the seminal paper "Fuzzy graphs" (1975), which has since received 910 citations (and it also cited in "Fuzzy morphisms between graphs").

Perchant and Bloch established a formalism for inexact graph matchings in "Fuzzy morphisms between graphs". The paper remains less influential with 61 citations.

Relation to other research

Prior-art

Rosenfeld was a leading researcher of image analysis and essentially established the field; among others writing the first textbook on the topic ("Picture Processing by Computer" in 1969, later followed by "Digital picture processing" in 1976, a book with 8547 citations).

Similarly, Perchant and Bloch have a background in image analysis.

Follow-up research

Bloch went on to applied research related to cognitive science and have among others co-authored the paper "Diffeomorphic demons: Efficient non-parametric image registration", which has received 1106 citations to date.

In general, follow-up research seem to be more oriented towards application rather than theory.

Demo

Time for a demo!

Example: source program compiled for three different machine architectures.

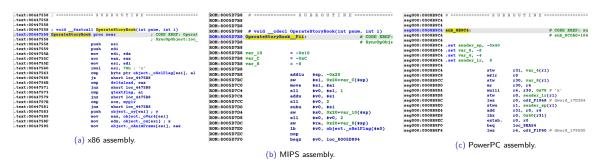


Figure: Machine code of the same source function in x86 (left), MIPS (middle) and PowerPC (right) assembly.

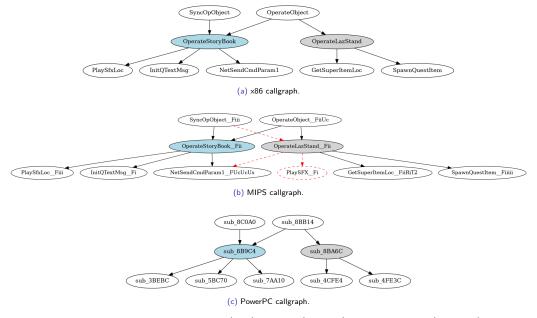


Figure: Corresponding callgraphs for x86 (top), MIPS (middle) and PowerPC (bottom) assembly.

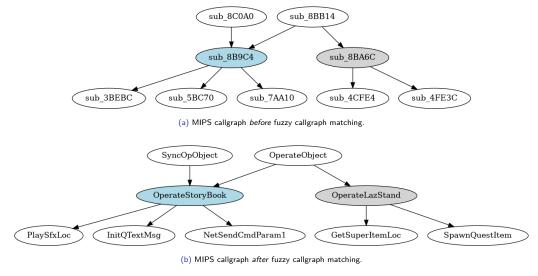


Figure: Results of fuzzy callgraph matching used to assign names to unknown functions.

The example source program has a callgraph with 2551 vertices and 6400 edges, illustrating the need for performant algorithms and the benefit of automating function identification.

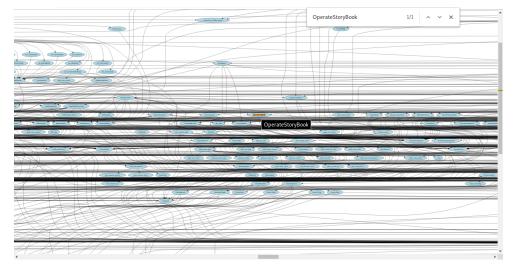


Figure: An extract of the callgraph of the source program.

For reference, this is the original source code of the C source function OperateStoryBook.

Figure: Original source code of the C source function OperateStoryBook.