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We Need Fuzzy Techniques to Design Successful Human-Like Robots

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Abstract

In this chapter, we argue that to make sure that human-like robots exhibit human-like behavior, we need to use fuzzy techniques – and we also provide details of this usage. The chapter is intended both for researchers and practitioners who are very familiar with fuzzy techniques and also for researchers and practitioners who do not know these techniques – but who are interested in designing human-like robots.

1 What Is the Main Objective of Designing Human-Like Robots

Most successful robots do not look like (and do not behave like) humans. For decades, robots have been successfully used in industrial applications to perform routine and/or dangerous tasks. Let us give a few examples.

- Robots have been used to perform manipulations in dangerous environments – e.g., after a disaster and building collapse, when the situation is too dangerous for human rescuers to enter.
- Robots have been used to help human astronauts to perform important repairs in space.

In all these example of successful applications, the design of a robot was determined by its desired functionality.

- Sometimes, some part of the robot somewhat resembles the corresponding part of a human being – e.g., there is some similarity between the robotic arm – which is used to grab, move, and manipulate objects – and a human arm.

- However, it is not that the designers wanted to simulate a human arm – if a more efficient but less similar design becomes available, engineers would gladly abandon the current similarity and switch to a new design.

The only reason why this similarity happens in actual robots is that some of the robotic tasks are similar to tasks that have been performed by humans and their ancestors for millions of years, and, as a result of millions of years of improving biological evolution, we humans developed (almost) optimal ways to implement these tasks. Naturally, designers – who also look for optimal ways to perform these tasks – come up with solutions resembling what nature has found by evolutionary trial-and-error.

Not all human features are optimal from this viewpoint: e.g., while we move on two feet, most robots use either wheels or more than two legs.

Since many possible human-like features are usually *not* implemented – they would make a robot less efficient – then why do we need to design human-like robots in the first place?

Why do we need to design human-like robots in the first place? If a robot works on its own – e.g., in assembling a car or in investigating the state of the collapsed building – functionality takes priority, we do not care whether this robot looks like a human being or not. But many robots are intended to collaborate with and communicate with people; for example:

- It is desirable to have robots that help medical doctors and nurses take care of patients.
- It is desirable to have robots that help elderly people and people with disabilities.
- It is desirable to have robots that would help astronauts explore distant planets.

In all these tasks, the success of using these robots comes not only from how well they perform their tasks, but also from how well they collaborate with and communicate with humans – and how convenient it is for humans to collaborate and communicate with these robots.

Humans are very skilled in collaborating and communicating with each other. We are much less skilled in collaborating with and communicating with objects which are different from us, be it animals or machines. So, to make it easier for people to collaborate with and communicate with robots, it is desirable to make these robots look like us – i.e., to design human-like robots.

In other words, there is only one major reason why we want to design human-like robots: to make it more convenient for humans to collaborate with and communicate with robots.

Robots should also behave human-like. For human-robot collaboration and communication to be successful, we need to make sure that robots not only *look* like us, but also that they *behave* like us.

This is a much more difficult task than creating outside resemblance.

What we do in this chapter. In this chapter, we provide arguments that the desire to make robotic behavior human-like naturally leads to the use of fuzzy techniques.

To explain why, let us briefly recall what are fuzzy techniques and how they have been used in control so far.

Comment. Readers who want to know more about fuzzy techniques are referred to [1, 3, 5, 10, 11, 14].

2 Fuzzy Techniques: A Brief Reminder

The origin of fuzzy techniques. Fuzzy techniques originated when Lotfi Zadeh, a renowned specialist in control and a co-author of the most successful textbook on control – so successful that the word z-transform is now used by all control students, practitioners, and researchers, most of whom have no idea that z comes from Zadeh – started thinking about how to make control more efficient.

Traditional control methods – in particular, techniques of optimal control – led to many successful applications, many successful designs of automatic and semi-automatic controllers. Somewhat puzzling was the fact that sometimes, the results of the supposedly optimal controllers were worse than the control provided by expert human controllers.

Of course, in reality, there was no puzzle, no contradiction. There is a straightforward explanation for this phenomenon: models of the corresponding systems used in designing an optimal controllers are approximate – since all models are approximate. And, of course, a control strategy that optimizes an approximate model may not be absolutely optimal for the actual system.

From this viewpoint, it looks like experts have some additional knowledge of the system, knowledge which has not yet been incorporated into the model. So, a natural way to improve the control is to elicit this knowledge from the experts.

Most experts are willing and eager to share their knowledge, but there is often a problem – the experts describe this knowledge not in precise terms (which would be feasible to add to the model), but rather by using imprecise ("fuzzy") words from natural language such as "small".

This fact is natural. For example, many folks know how to drive a car. However, if someone asks you what do you do if you are traveling on a highway at the speed of 100 km/h and a car 10 meters in front of you slows down to 95, a natural answer will be: I break a little bit. Very few people will able to explain with what exactly force they press the break pedal and for exactly how long. And this is typical.

Lotfi Zadeh came up with a technique to describe this knowledge, technique that he called *fuzzy*.

What are fuzzy techniques: a brief reminder. In contrast to precise statement like "speed is greater than 90 km/h" which are always either true or false, a typical natural-language statement like "the car is going fast" is not precise. For some values of the car speed, this is absolutely true, for some it is absolutely false, but for intermediate values, the expert him/herself is not 100% sure whether this statement is true or not.

To describe this uncertainty, a natural idea is to ask the expert to describe his/her degree of confidence – that the speed is fast – by selecting a number on some numerical scale: e.g., on a scale from 0 to 1, in which:

- 0 means absolutely false,
- 1 means absolutely true, and
- intermediate values correspond to uncertainty.

This is something we all do when we answer surveys, this is something students do when they evaluate their instructors, etc.

This way, for different values of the corresponding quantity x, we get a degree $\mu(x)$ to which the corresponding statement (like "x is fast") is true. Of course, there are infinitely many possible values of the quantity, and we can only ask finitely many questions. So, we need to use some interpolation – e.g., linear interpolation – to get the values $\mu(x)$ for all x. The resulting function $\mu(x)$ is called a *membership function*.

This is only the beginning: expert rules usually have several conditions. For example, we can have a rule "if a car in front is close and it slows down a little bit, then press the break pedal a little bit". To describe the consequences of this rule, it is not sufficient to find the degree to which, for the given distance d, the car is close, and the degree to which, for a given change Δv in speed, the car in front slowed down a little bit – we also need to know the degree to which the entire "and"-statement "the car in front is close and it slows down a little bit" is true.

Theoretically, we can get this degree by asking the same expert to mark his/her degree of confidence in this "and"-statement for all possible pairs $(d, \Delta v)$ – and if there are three or four conditions, for all possible triples, quadruples, etc. However, in practice, this is not possible. Even if we consider 10 values for each quantity, for quadruples, there are 10^4 combinations of these statements – and it is not possible to ask 10000 questions just to find the meaning of each of the expert's rules.

Since we cannot elicit the desired degrees of such "and"-statements $A \,\&\, B$ directly from the expert, we need to estimate these degrees based on whatever information we have: namely, on the expert's degrees of confidence a and b in statements A and B. The algorithm that estimates the expert's degree of confidence in the composite statement $A \,\&\, B$ based on the values a and b is called an *"and"-operation* (or, for historical reason, a t-norm). We will denote its result by $f_{\&}(a, b)$.

Similarly, an algorithm that estimates the expert's degree of confidence in the composite statement $A \vee B$ based on the values a and b is called an *"or"-operation* (or, for historical reason, a t-conorm). We will denote its result by $f_{\vee}(a, b)$.

Once we selected the "and"- and "or"-operations, we can translate the expert rules into a precise control strategy that transforms the inputs $x_1, \ldots, x_n$ into a control value u. Indeed, suppose that the expert has the following r rules containing imprecise terms A_{ij} and B_i:

- If x_1 is A_{11}, ..., and x_n is A_{1n}, then u is B_1.
- ...
- If x_1 is A_{r1}, ..., and x_n is A_{rn}, then u is B_r.

These rules are usually called *fuzzy rules*.

These rules mean that u is a reasonable control for given values $x_1, \ldots, x_n$ if one of these rules is applicable, i.e.:

- either x_1 is A_{11}, ..., x_n is A_{1n}, and u is B_1;
- ...
- or x_1 is A_{r1}, ..., x_n is A_{rn}, and u is B_r.

We can elicit, from the experts, the membership functions $\mu_{ij}(x_j)$ and $\mu_i(u)$ corresponding to the terms A_{ij} and B_i. If we use an "and"-operation $f_\&(a, b)$ and an "or"-operation $f_\vee(a, b)$, then the degree $\mu(u)$ to which u is reasonable is equal to

$$\mu(u) =$$
$$f_\vee(f_\&(\mu_{11}(x_1), \ldots, \mu_{1n}(x_n), \mu_1(u)), \ldots, f_\&(\mu_{r1}(x_1), \ldots, \mu_{rn}(x_n), \mu_r(u))).$$

For manual control or decision making, this formula allows us to provide recommendations for the decision maker.

In the case of automatic control, we need to select a single value $\bar{u}$. A reasonable idea is to select a value which is close to all possible value of control. The degree of confidence μ can be naturally interpreted as saying that out of N cases, we would make this conclusion $N \cdot \mu$ times.

So, in the simplified case when we have finitely many possible control values $u_1, \ldots, u_m$, then we have the following system of approximate equations:

$$\bar{u} \approx u_1 \quad (N \cdot \mu(u_1) \text{ times});$$
$$\ldots$$
$$\bar{u} \approx u_m \quad (N \cdot \mu(u_m) \text{ times}).$$

In other words, we want to find a single value $\bar{u}$ for which the tuple $(\bar{u}, \ldots, \bar{u})$ is as close as possible to the tuple

$$(\mu(u_1), \mu(u_1), \ldots, \mu(u_m), \mu(u_m)).$$

Minimizing the distance between the two couples is equivalent to minimizing the square of this distance, i.e., the sum

$$\sum_{i=1}^{m} N \cdot \mu(u_i) \cdot (\bar{u} - u_i)^2.$$

Minimizing this quantity is, in its turn, equivalent to minimize the same quantity divided by a constant N, i.e., the sum

$$\sum_{i=1}^{m} \mu(u_i) \cdot (\bar{u} - u_i)^2.$$

In the continuous limit, we get $\int \mu(u) \cdot (\bar{u} - u)^2 \, du$. Differentiating this expression with respect to the unknown $\bar{u}$ and equating the derivative to 0, we conclude that

$$2 \int \mu(u) \cdot (\bar{u} - u) \, du = 2 \left(\bar{u} \cdot \int \mu(u) \, du - \int u \cdot \mu(u) \, du \right) = 0,$$

hence

$$\bar{u} = \frac{\int u \cdot \mu(u) \, du}{\int \mu(u) \, du}.$$

This formula is known as *centroid defuzzification*.

Comments.

- It is known that to describe possible values of each quantity, people select between 5 and 9 different terms like "small" or "big"; this corresponds to the well-known "seven plus minus two rule"; see, e.g., [6, 12]. How many values we use depends on the person – it is 5 for some folks, 9 for others, in between values for the rest.

- What we described is the basic way of translating experts' natural-language statements into an exact control strategy. In practice, there are more sophisticated techniques that lead to a more accurate description of expert rules.

  Let us give just one example. It is reasonable to take into account that an expert often cannot describe his/her degree of confidence in a statement by a single number – no one can distinguish between degree of confidence 0.509 and degree if confidence 0.510. It is more reasonable to ask an expert to provide the whole interval of possible values of this degree – which leads to interval-valued control, etc.

  We can also use machine learning and/or genetic algorithms to come up with appropriate interpolation techniques.

  In general, all these techniques are known as *fuzzy techniques*, not only the above-described basic ones – as long as we understand fuzzy techniques as techniques that allow us to translate natural-language rules into a precise control strategy.

3 Fuzzy Techniques: Successes and Limitations

Successes. Fuzzy techniques have been very successful in many applications, especially in applications where the objective function itself is fuzzy; e.g.:

- how to design a train with the maximally smooth ride,
- how to design a rice cooker that cooks the most tasty rice, etc.

Fuzzy techniques have also been very useful in more traditional engineering applications, where a straightforward formalization of available imprecise expert knowledge leads to reasonably good automatic controls.

Limitations. The main limitation of fuzzy techniques is that the resulting control is usually not optimal.

Indeed, if we, crudely speaking, only consider 5 to 9 different possible values of each input, we then cannot compete with more thorough optimization techniques in which we can find the optimal control value for each of the numerous possible values of the inputs.

How is fuzzy control used. Because of this limitation, fuzzy control is usually used:

- either on the initial stage, where we need to design *a* controller,
- or – on the later stages – in combination with more traditional techniques: the more traditional techniques are used to take care of precise defined objective functions, while fuzzy techniques deal with subjective difficult-to-formalize objective functions like smoothness or taste.

4 So How Should We Make Robotic Behavior More Human-Like: General Idea

How do we describe our own behavior. What does it mean for a behavior to be human-like? It means that robots behave the same way we do.

How do we ourselves behave? A natural way to answer this question is to ask us how we behave. And this is exactly what we do when we try to translate human behavior into a precise control strategy: we ask experts how they do it. As we have mentioned, what experts do as a reply is provide us with imprecise rules – corresponding to combinations of 5-9 words for each input. In other words, when we describe our own behavior – we use what is called *fuzzy rules.*

Maybe this is a biased description and our actual behavior is different? Not really: it turns out that many sub-optimal features of our behavior – features well-studied by psychologists (see, e.g., [2]) can practically all be explained if we take into account the fuzzy-rule model of our behavior; see, e.g., [4].

So let us use fuzzy techniques in designing human-like robots. The fact that our own behavior is well described by fuzzy rules leads to a natural conclusion:

- *if we want robots to show human-like behavior,*
- *we need to use fuzzy control!*

This goes contrary to the usual robotic design, where a lot of optimization is implemented – but this is the whole point: we need understandable, human-like behavior, *not* necessarily optimal control.

- Explainability is what many of us want from AI-based bank systems deciding whether to give us a loan or not.
- Explainability is what we expect from human-like robots.

In situations when we do not need explainability, we do not need to make robots human-like at all, neither in the way they look nor in the way they behave.

Let us illustrate on an example of planning a spaceflight. If we want an automatic space mission to go to several planets, a natural idea is to go to the nearest planet, they move to the next one, etc. This is reasonable and understandable, but the optimal trajectory is often quite different: to save fuel, the optimal way is to follow some weird non-intuitive trajectory that uses gravitational pull from nearby planets to perform needed changes in the spaceship's trajectory without spending too much of the limited amount of fuel. In these terms, what we want from a human-like robot is *not* such an optimal trajectory, we want a not-so-efficient trajectory that we will be able to understand.

Similarly, when students learn new material, they are much more productive when they can understand *why* they are studying, e.g., this particular math class – and not as productive if they are simply told that this leads to the best possible knowledge at the end, without any additional explanations.

Our hope. Our hope is that fuzzy control will be intensively used in designing human-like robots.

5 How to Make Robotic Behavior More Human-Like: Technical Details

Now that we have described the main idea, let us provide some details about how exactly this idea should be implemented.

Human-like robots should be individualized. We want human-like robots' behavior to be explainable – but at the same time, under this constraint, we want this behavior to be as optimal as possible.

Of course, the more values (5 to 9) of each quantity we use, the more parameters we have in our control strategy and thus, the better control we can achieve. From this viewpoint, we need to use as many values as possible.

However, as we have mentioned, understandability depends on the user:

- for some users, understandability is limited to 5 levels,
- others users can gain understandability even if we have 9 levels.

Thus, for each user, we need to select, for each input, the number of levels corresponding to this particular user:

- 5 levels for some users,
- 6 levels for other users,
- ..., all the way to 9 levels for some users.

In other words, human-like robots must be individualized.

- It is possible – but not optimal – to use a 5-level robot with a higher-level (e.g., 9-level) patients.
- However, if we try to do the opposite – e.g., use a 9-level robot with a 5-level patient, this will make the robot's behavior less explainable and thus, defeat the whole purpose of human-like robots.

Which "and"- and "or"-operations should we use when designing human-like robots. When we elicit knowledge from experts, as we have mentioned, the corresponding degrees of certainty come with some uncertainty:

- what can be one time described as 0.6,
- the same expert next time can describe as 0.7,

since in reality, there is a whole interval of possible values describing the expert's opinion.

It is desirable to minimize the effect of this uncertainty on the resulting robot's behavior. Since an important step in fuzzy control is estimating the degrees $f_\&(a,b)$ and $f_\vee(a,b)$ based on the known values a and b, we therefore need to minimize the changes in the values of these functions based on changes in a and b. How can we do it?

Since the robot needs to perform many tasks, a natural idea is to minimize the overall effect of this uncertainty in all these tasks, i.e., to minimize the average effect of these changes. In mathematical terms, we need to select the most robust operations.

A natural way to describe these changes is to add random deviations Δa and Δb to the original values and consider the mean square value of the difference

$$f_\&(a+\Delta a, b+\Delta b) - f_\&(a,b),$$

i.e., equivalently, the smallest possible value of the integral

$$\int_0^1 \int_0^1 E\left[(f_\&(a+\Delta a, b+\Delta b) - f_\&(a,b))^2\right]\, da\, db,$$

where $E[\cdot]$ stands for expected value – and similarly for the "or"-operation.

It turns out that the smallest possible value of this mean square difference is attained when $f_\&(a,b) = a \cdot b$ and $f_\vee(a,b) = a + b - a \cdot b$, i.e., when we use what in fuzzy techniques is called algebraic product and algebraic sum; see, e.g., [9, 10].

Alternatively, instead of aiming for overall robustness – and allowing a few actions to be possible less robust – we can aim for making each action robust. In this case, instead of minimizing the *average* difference, we should minimize the *worst-possible* difference

$$\max_{a,b} |f_{\&}(a+\Delta a, b+\Delta b) - f_{\&}(a,b)|\,.$$

In this case, the optimal "and"- and "or"-operations are $f_{\&}(a,b) = \min(a,b)$ and $f_{\vee}(a,b) = \max(a,b)$ [7, 8, 10].

Comment. These may be not always the operations leading to the optimal control – see, e.g., [13] for optimal operations – but, as we have mentioned several times, the main objective of controlling a human-like robot is *not* to come up with the optimal control, but to come up with an *understandable* control (to be more precise, a control which is optimal among understandable controls).

Control of human-like robots should not always be limited to fuzzy control. In everyday behavior, robots should behave like humans – in particular, they should show human-like behavior – and, as we have argued, for this, we need to use fuzzy rules and fuzzy techniques.

However, in many cases, these robots have an additional functionality that goes beyond user comfort. For example, a robot taking care of elderly patients should bring them medicine and food, should help them feel better – but in the case of an emergency, this robot should be able to react as fast and as efficiently as possible. If a robot needs to move to bring the needed emergency help to a patient at risk of dying, it should not use a suboptimal explainable control strategy, it should get there as fast as possible.

For this purpose, ideal human-like robots should have *two* control strategies:

- a control strategy based on fuzzy rules for everyday situations and
- an optimal (or at least as-optimal-as-possible) strategy for emergency situations.

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