I. Troch, F. Breitenecker, eds. ISBN 978-3-901608-35-3

FUZZYPICS – A VISUAL APPROACH ON MODELING AND COMPUTING VAGUE KNOWLEDGE

J. Fischer[1], T. Wiedemann[1]
[1]Hochschule fuer Technik und Wirtschaft, University of Applied Sciences, Dresden, Germany

Corresponding author: J. Fischer, T. Wiedemann, HTW - University of Applied Sciences, Departement Information Technologie and Mathematics,
01069 Dresden, Friedrich-List-Platz 1, Germany, jakob.fischer@coeps.net, wiedem@informatik.htw-dresden.de

Abstract. The paper introduces a visual approach on modelling vague knowledge. The approach uses images, called Fuzzypics, to model human knowledge or generated models and supplies it directly as a computable bitmap. Knowledge engineering is done by visual means rather than linguistic terms to avoid inconsistencies in the Fuzzy-Rule sets and supply the holder of the knowledge with an intuitively understandable concept for knowledge representation. Therefore Fuzzypics do not require the explicit definition of Fuzzy-Sets but can handle them. The bitmap works as the knowledge base for a computational reproduction of that knowledge. Since the inference procedure is a simple operation on the bitmap we buy computation rate at the expense of memory. Fuzzypics can be arranged in sequences to allow sophisticated inference models. The presented concept can interlink between a crisp model and an extensive fuzzy model, since the use of it is highly scalable. The paper gives a overview of the idea of visual modelling with Fuzzypics. Suboptimal characteristics of common linguistic approaches are pointed out and lead to a formal definition of Fuzzypics and their use. In order to clarify the concept, examples of human decision making and technical problems are given. Besides the use for simulation tasks and visual knowledge engineering, the practical use for automated quality control is pointed out. Fuzzypics are presented as a concept that understands itself as an high-speed add-on to the wide range of possibilities to model and process vague knowledge.

1 Introduction and Motivation

1.1 Common Problems of modelling human decision making

In order to simulate processes or systems involving human beings, one needs to model human decisions. Depending on the level of abstraction, the more or less details of the decision-process have to be mapped to a computable model. The higher the level of abstraction is chosen, the less detail has to be modelled.

Since the idea of Fuzzy-Logic was introduced [8] (cp. [2], [7]) there are well defined mathematical properties to handle vague information expressed by humans. The concept of Linguistic Approximation (cp. [1]) helps to bind these statements to numerical values by using linguistic terms [9] as Fuzzy-Sets.

Consider a simple set-up of decision making from the field of healthcare. In order to determine a well-balanced number of dentists in a medical institution, we need the decision if a person who suffers from toothache will visit the dentist office or not. We use two main influences "Toothache" and "Fear from the dentist" as inputs to make the decision, claiming that a decision is a conclusion deduced from one or many inputs. The premise for the variables are "Low", "Medium" and "High".

In our example a human feels pain and might communicate it by using linguistic terms like the ones given. But there is no finite numeric scale we can attach the strength of pain to. Even if we define a scale from 1 to 10 with 10 being the worst pain imaginable we still cannot define bounds. What kind of agony is conceivable? Pains are something entirely different for someone who suffered a severe injury than someone who only knows headache. And what is severe pain? Comparing grades as a different way of defining Fuzzy-Sets will probably fail for lack of volunteers. The same problems occur when defining the Fuzzy-Sets for the parameter "Fear".

Therefore we need a different proceeding. One might think that a definition of sets like "greater than" could lead to a proper solution. Let someone visit the doctor's office when the value of pain is greater than the value of fear. But then we would have to directly compare the grade of "Pain" and the grade of "Fear" which have different semantics. We can build a simple model by defining linear scales for both influence using the given linguistic terms, but we have to accept a high level of abstraction.

In this case a different suboptimal situation occurs. If we define a comparing rule set with the pattern "If the Pain is greater than the Fear then visit the dentist's office" and vice versa, we will face a undefined situation when both influences are equal, irrespective of the step width of the scale. So what happens if "Pain" is "High" and "Fear" is "High"? Surveying the situation from the perspective of real life, it is probable that a person who suffers from severe pain will eventually visit the doctor, regardless how much fear is felt. One can call this influence "Sanity".

1.2 Linguistic Approximation of emotions

For modelling decisions mentioned above, we need to get information from potential patients. So the first task is the determination of the influences. The problem therein is that we can not determine the finite number of influences on a real world decision, at least for decisions based on emotions. Not for nothing we use expression like "getting up on the wrong side" to say that we can not identify the motives of a certain behaviour we can still notice. In order to model behaviour, due to the inherent characteristics of a manageable model, we have to limit the influences in hope to create incomplete but valid design.

Following the principle of Fuzzy-Logic and Fuzzy-Sets, human knowledge can be modelled by defining Fuzzy-Sets based on linguistic terms. Human experts can combine them with rules and attach them to other Fuzzy-Sets. The concept of retrieving expert knowledge by using sets is perfectly applicable to technical problems where we apply grades of member ship to unique values, such as speed or temperature. Disregarding limitations like complexity of handling, the more Fuzzy-Sets are used the more precise is the resulting rule base. In other words, the more not redundant linguistic Fuzzy-Sets one applies to a variable, the narrower the sets become, the more precise the conclusion can be distinguished.

To meet the requirements of a well comprehensible decision set-up, further parameters will be necessary in our model. The parameter "Sanity" will influence the decision equally as the other two parameters do. To express this fact, the parameter must be added to the decision once the other two parameters reach a certain level. This can be accomplished sticking to the rules of Fuzzy-Logic, by adding the parameter with the OR-operator [8]. In case other necessary parameters have to be introduced, modelling such easy decision becomes a rather complicated task, due to a rapidly growing amount of rules to be evaluated. For a fast computable process this approach is imperfect.

If it is not possible to determine proper Fuzzy-Sets of variables one has to find other ways to model these senses. The question arises if the concept of sets is indispensable for this task.

To define the scope of the approach described in this paper, it is necessary to note that the modelling of human emotions was the catalyst for the work done. For Multi-Agent-Simulations Fuzzy-Logic has been successfully used to simulate human emotions in computable models (cp. e.g. [10],[11] or [12]). These models basically aim to equip a sophisticated Agent with emotional driven behaviour, emphasizing psychological theories. The approach at hand focuses on the the rapid decision making rather than modelling the context of emotions.

1.3 Basic thoughts on Fuzzy-Sets and knowledge engineering

Having a discrete system of Fuzzy-Sets for the sake of simplicity, continuing with narrowing the sets by distinguishing more sets for a single variable, Fuzzy-Sets become singletons and crisp sets again once the step size of the variable is reached.

Theoretically, a omniscient expert is capable of combining all combinations of input singletons to the appropriate output values. This omniscient expert makes the concept of sets dispensable because there is nothing needed to group into a set. Neither into crisp or fuzzy sets. The result is a perfect controller in sense of reproducing human decisions, not calculating the output by solving an equation but by processing rules out of a set of rules for every combination of inputs. Since this is blank theory, we use the concept of Fuzzyfication, Fuzzy-Inference and Defuzzyfication to compensate for the impreciseness of human beings.

It is often cited as an example for an explanation of Fuzzy-Logic that humans do not think in measures but in overlapping sets. For instance a car driver does not decelerate because of knowing distance, speed and time till crash, but because he just knows that its best to brake. We need the sets, fuzzy or crisp, for the communication between a model and an expert. But do we use them deliberately to act? Does the experienced driver think about what he is doing? Well, it is probably a question of perception, but it leads to the idea of knowledge engineering without the genuine use of sets to create a rule based model of vague knowledge.

1.4 Knowledge engineering with images

Storing knowledge in some kind of representation is the base for the process of inference (cp. [3] or [14]). The idea of using pictures as a representation is not new. It is, e.g. in [15], (S.24) mentioned as a field for further research. Visual representation is today a quasi-standard to clarify subject in oral representation. Humans have brilliant ability to understand with their visual senses, so visualisation of data is a stand alone field of research (cp. [5]). Furthermore, drawing and sketching is an ability most people learn from childhood on. So it suggests itself to use this form of representation for knowledge acquisition.

A visual representation must meet some basic requirements:

Processability. A visual representation must be designed in a way that a computer can process it. This includes an invariant file format, colour space and shape. The image must follow a invariant pattern the computer can recognise.

Independency of context and form. The basic set of algorithms supplied to the computer must be sufficient to process the image independently from the context of the image.

Comprehensibility. In generals (cp. [3]) there are three persons, who are involved in the process of knowledge engineering. The expert, the knowledge engineer and the user. Especially the first mentioned must be able to understand the concept of creating the images, as well as how his knowledge has to be inserted into the image.

Connectivity. It must be possible to link the images in a way that allows an inference.

In the one at hand and future papers, we try to extend the concept of visual knowledge representations. The approach seems very interesting in the actual state of knowledge engineering. It could be a extension and alternative to existing technologies like Neuronal Networks and is referred to as "Fuzzypic" [6].

2 Fuzzypics

2.1 Introduction to the concept of Fuzzypics

The derivation of the subject using the example with human emotions was the problem faced first. The original decisions to be made were questions from the field of healthcare, where human emotions have to be modeled. The basic concept is not bound to modelling human emotions or healthcare simulations. Technical inputs can be processed in an appealing way as well. Furthermore, Fuzzypics do not even have to be generated by a human expert as will be shown. An automated generation is possible as well.

The basic shape of a Fuzzypic is a two dimensional bitmap. Each dimension represents the scale for a variable. So, a Fuzzypic is defined by two input variables and values of output variables. Fuzzypics are used as lookup arrays, so the decision process is a single operation on the computers memory of few nano-seconds. The Fuzzypic-Inference gets two variables as input and returns the colour value as value for the conclusion. So, a simple Fuzzypic with the inputs "Toothache" and "Fear from the dentist" will deliver the event "To go to the dentist" a as bivalent choice or a probability of doing so.

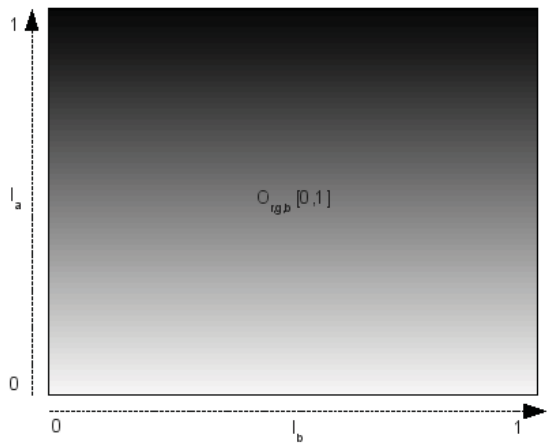

Figure 1: Basic set-up of a Fuzzypic

2.2 Formal definitions of Fuzzypics

The basic shape of a Fuzzypic, called a normalised Fuzzypic, is a two dimensional bitmap, which is defined by

$$Fp_{(I_A,I_B,O)}, \tag{1}$$

where I_A and I_B are subsets of ordered input values out of the closed interval $[0,1]$

$$I_A \subseteq [0,1] \tag{2}$$
$$I_B \subseteq [0,1] \tag{3}$$

and O the image set of the mapping

$$f_{fuzzy} : I \longrightarrow O \tag{4}$$

$$I = I_A \times I_B. \tag{5}$$

O is a set of three dimensional vectors $o_{r,b,g}$, with

$$\{o \in O | 0 \leq r,b,g \leq 1\}. \tag{6}$$

The indices r,g,b stand for the colour values Red, Green and Blue. The normalised Fuzzypic contains only gray scale values.

Gray scale values are represented by equal values of all three colour channels, so

$$r = g = b \tag{7}$$

allows us to refer to $o_{r,g,b}$ as o.

The function f_{fuzzy} is the specification that assigns a vector o to each element of the set I. To supply a notation for the subset of O as set of output values $o \in O$ assigned by f_{fuzzy} to the specific location $I_{A,B}$, in this paper it will be referred to as $\zeta_{Fuzzypic}$.

Fuzzypics do not show Fuzzy-Sets as membership functions do, at least normalised Fuzzypics, they show grades of output values assigned by f_{fuzzy}. Nevertheless $\zeta_{Fuzzypic}$ can be handled with a similar notation and similar operators as Fuzzy-Sets. To avoid misapprehension and allow better communication for set-ups of Fuzzypics, first operators are introduced. There are a lot of possible operations on Fuzzypics thinkable, but in this paper, operators are generally used, to accentuate main characteristics of Fuzzypics.

Following most fundamental operators can be assigned to Fuzzypics. Consider two Fuzzypics $X_{(I_{XA},I_{XB},O_X)}$ and $Y_{(I_{YA},I_{YB},O_Y)}$.

$$X = Y \tag{8}$$

when following conditions are true:

$$I_{XA} = I_{YA} \tag{9}$$

$$I_{XB} = I_{YB} \tag{10}$$

$$\zeta_{X_{A,B}} = \zeta_{Y_{A,B}}. \tag{11}$$

If one of the three conditions is not true, one can write

$$X \neq Y. \tag{12}$$

If one Fuzzypic contains another, we can say:

$$X \subset Y \tag{13}$$

when:

$$I_X \subset I_Y \tag{14}$$

$$\zeta_{X_I} \subset \zeta_Y \tag{15}$$

$$o_X(a,b) = o_Y(a+da, b+db) \tag{16}$$

where da, db are the offsets between X and Y.

A definition, only affecting the basic set-up, that two Fuzzypics are comparable is the 'compatibility'. The two Fuzzypics input variables and the context of the output variables are equal and cover the same range. Two Fuzzypics X and Y are called "compatible", when true:

$$I_{XA} = I_{YA} \tag{17}$$

$$I_{XB} = I_{YB} \tag{18}$$

$$\zeta_{X_{A,B}} \neq \zeta_{Y_{A,B}}. \tag{19}$$

We can see that "compatibility" and "equality" differ just in one attribute. The notation for the characteristics of two compatible Fuzzypics X and Y with is:

$$X \leftrightarrow Y. \tag{20}$$

A characteristic Fuzzypics have, is the defined maximum value of the set o. This permits an operation on one Fuzzypic. The complement

$$\neg X. \tag{21}$$

The operation affects ζ_X but does not affect the input variables. For every o assigned to I

$$o_{\neg X_i} = o_{max} - o_i. \tag{22}$$

The most fundamental connective operations in classical set theory, the union and intersection, are available for Fuzzypics as well. Like the corresponding operators in Fuzzy-Theory have more than one implementation (cp. [2] for further reading), this is possible for Fuzzypics as well. They are for now defined as minimum and maximum operator according to [8], but can only be used on normalized Fuzzypics without further consideration.

The Fuzzypic intersection for the Fuzzypics X and Y with $X \leftrightarrow Y$ is defined for all elements o as:

$$Z_{(\zeta_{X\cap Y})} = X \cap Y \tag{23}$$

$$o_{X\cap Y} = min\{o_X, o_Y\}. \tag{24}$$

The Fuzzypic union for the Fuzzypics X and Y with $X \leftrightarrow Y$ is defined for all elements o as:

$$Z_{(\zeta_{X\cup Y})} = X \cup Y \tag{25}$$

$$o_{X\cup Y} = max\{o_X, o_Y\}. \tag{26}$$

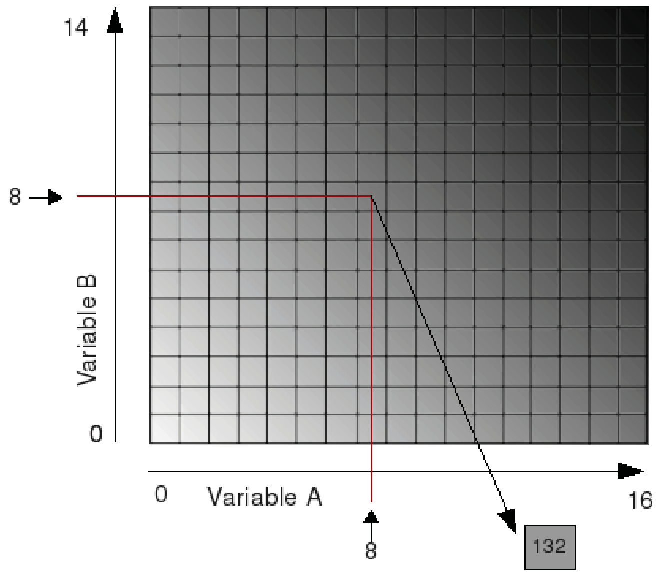

Figure 2: Schematic illustration of the inference with Fuzzypics.

For the process of knowledge engineering with Fuzzypics operators for addition and subtraction and multiplication of two or more Fuzzypics have to be defined. It is essential that $X \leftrightarrow Y$.

The operator $+$ for all elements o is given as:

$$Z_{X+Y} = o_X + o_Y. \tag{27}$$

The operator $-$ for all elements o is given as:

$$Z_{X-Y} = o_X - o_Y. \tag{28}$$

The operator $*$ for all elements o is given as:

$$Z_{X*Y} = o_X * o_Y. \tag{29}$$

2.3 Generation of Fuzzypics

The concept of a Fuzzypic is based on the thought that if it is not possible to model vague information by the means of linguistic terms, it still might be possible to model it by using graphical representations. One way of creating is to have the Fuzzypic designed by the knowledge engineer and filled by the expert. This can be done with different tools. Even pencil and paper are sufficient. In this case it has to be scanned and over-worked with digital image manipulation software to be processable by the computer.

Filling the Fuzzypic with values allows an accurate assignment of the result values. The expert can make very small distinctions but at the same time look figuratively from the distance since he overlooks the whole set-up.

This set-up differs from the concept of the knowledge engineering with Fuzzy-Sets. Where Fuzzy-Sets focus on the definition of a single set or a group of sets, Fuzzypics show the whole picture of the decision set-up. At this point we come back to the thought that the concept of sets might be dispensable. It's safe to say that the knowledge engineer will use sets to point out certain areas of special interest in the Fuzzypic. But still, the borders between sets become indistinct.

Due to the short time of research done on the use of Fuzzypics, it is too early to evaluate all aspects of this procedure. But first tests show that even people who do not have an insight into the concept of knowledge engineering or knowledge based models of decision making at all, can fill an empty Fuzzypic.

It has to be emphasized that a Fuzzypic is capable of representing human knowledge. As mentioned before, we can not be sure if the decision is only influenced by the parameters "Pain" and "Fear". We can not be sure, but we can appoint them to be the most significant reasons. There will be more influences, but if we include all of them into the model, the decision process becomes confusing and hardly maintainable. To draw on a picture, we could figure the variables with their relative grades as fixed boundaries of a plane, knowing that the answers of the expert lie not necessarily on this plane but close to it in the third dimension. For the representation of the knowledge the answers are projected onto the plane, what results in a Fuzzypic. People who fill out Fuzzypics do take more influences into account that the ones supplied by the two input variables. So Fuzzypics cover less important influences on the decision, because the experts focus on the whole set-up of the decision.

There are basically three different ways Fuzzypics can be generated using the computer. They differ in the way the information is supplied and how the Fuzzypic is to be used.

Full definition. The function f_{fuzzy} is given in a mathematical or algorithmic manner. On this basis the Fuzzypic can be generated by the computer, e.g. 'Figure 3'.

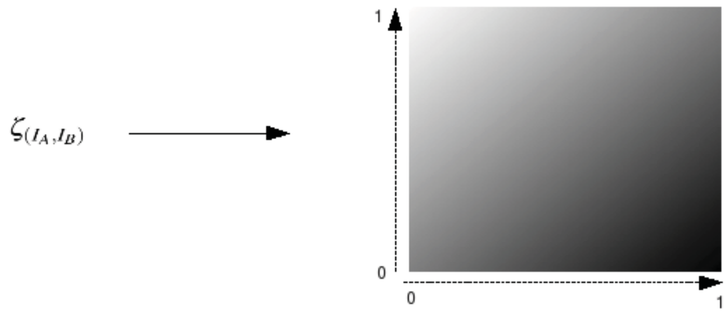

Figure 3: Fuzzypic, generated with a calculation specification

Incomplete definition. Only certain areas of reliability are given. An appropriate algorithm, like the bilinear interpolation must be chosen (cp. [4], [13]). Standard image processing applications provide a wide range of tools that can be used to create and alter Fuzzypics, e.g. 'Figure 4'.

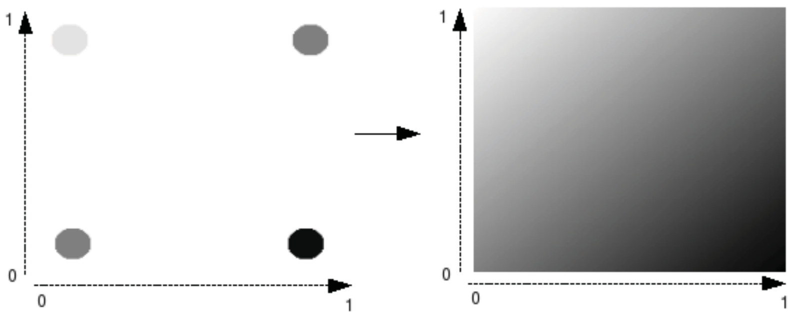

Figure 4: Fuzzypic, generated by using interpolation algorithms

Extension with random values The content of the Fuzzypic can be randomized, to extend the use of it. Therefore the elements o take random values of a chosen distribution in certain areas of interest. This set-up is useful for generation random events, e.g. when it is necessary to create a smooth transition in a Fuzzypic which offers only a bivalent choice. 'Figure 5' shows such Fuzzypic.

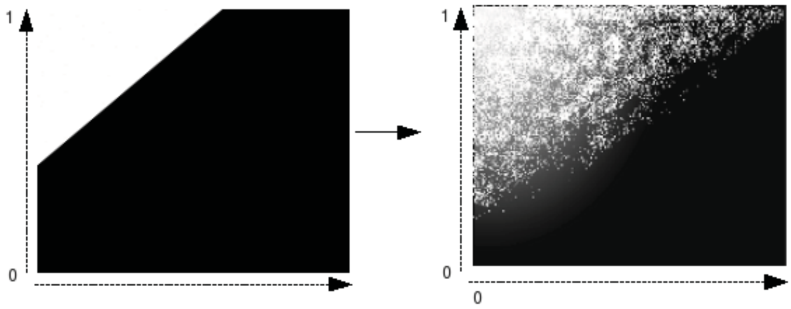

Figure 5: Fuzzypic, extended with random data

The method of generating the Fuzzypic has to be clearly distinguished from the procedure of creating the Fuzzypic by the means of knowledge engineering. While the last mentioned is a representation of human knowledge where the Fuzzypic has the characteristic of a medium for communication between humans and machines, the generated one is just a computable fast representation of a given decision process.

2.4 Knowledge engineering with Fuzzypics

When human made decisions are to be modelled, more than one Fuzzypic will be used, whereas the different Fuzzypics meet the condition of compatibility. E.g. a certain group of patients can be ask to fill a Fuzzypic with an equal set-up to get a wide range of opinions. For connecting the various Fuzzypics four different basic procedures are given in this paper.

According to the arithmetic average:

$$Z_{result} = \frac{1}{n}\sum_{i=1}^{n} X_i. \tag{30}$$

According to the geometric mean with all $o_X > 0$:

$$Z_{result} = \sqrt[n]{\prod_{i=1}^{n} X_i}. \tag{31}$$

According to (24):

$$Z_{result} = \bigcap_{i=1}^{n} X_i. \tag{32}$$

According to (26):

$$Z_{result} = \bigcup_{i=1}^{n} X_i. \tag{33}$$

Where $\{i \in \mathbb{N}\backslash 0\}$ applies for all listings.

This procedures are appropriate for the example given above, where we model the decision to go to the dentist or not. However, using this operations on different Fuzzypics causes a loss of information.

While the normalized Fuzzypic is useful to show formal operators, it can not be used for inferences in applications in the given shape. For the employment the normalized Fuzzypic has to be transformed in a discrete form. The ranges of the input variable I_A and I_B have to be set, as well as O. For input variables like "pain" or "fear" a relative scale might be applied, other Fuzzypics handle absolute input values. It depends on the context of the model. 'Figure 6' in example uses a absolute input of 20 values. Applied in a simulation, the value can be set on the course of calculation or by using other Fuzzypics. Therefore I_A, I_B and O have to be extended by a minimum and a maximum value, to $I_{A_{min,max}}$, $I_{B_{min,max}}$ and $O_{min,max}$, with

$$\{i, o, min, max \in \mathbb{N}\}. \tag{34}$$

For the distinction of the three different colour channels some operations on Fuzzypics have to be extended. Both operators $\cap$ and $\cup$ have to applied to all three dimensions of the output vector. For exemplification, in detail the operator $\cup$ for all elements o:

$$o_{X_{channel} \cup Y_{channel}} = max\{o_{X_{channel}}, o_{Y_{channel}}\}. \tag{35}$$

The calculation specifications (27) have to be extended with the following rule:

$$o_{Z_{channel}} = o_{X_{channel}} + / - / * o_{Y_{channel}}. \tag{36}$$

It has to be mentioned that according to the characteristics of the set 0 from 34, it has to be made sure that the elements o fit into the applied range of the Fuzzypic after processing operations, since colour values are natural numbers.

The output values of a Fuzzypic are the colour values. As colour space the RGB (cp. [4], [13]) model is used. This allows easy algorithmic handling of Fuzzypics, since the Fuzzypic is stored basically as a three dimensional array. As described either the value grey, where the three colour channels have the same value, or the distinct colour values reed, green and blue. For bivalent decisions the set O has only two values. The example given in 'Figure 7' uses positive and negative values. Negative values are not accepted for colours. The minimal value accepted is zero. So it is necessary to shift the resulting value in a way that the minimal value fits positive values. This step needs additional computation for the inference with a Fuzzypic.

The semantic content of set O can be of different kinds. A possibility to express the result of the inputs "Pain" and "Fear" is i.e. the probability of a person visiting the doctors office. The resulting rule of the Fuzzypic is therefore "If Pain = x and Fear = y then the probability of going to the dentist is z".

The discrete characteristic allows $2^8 = 256$ or $2^{16} = 65536$ different output values per colour channel, depending on the bits used. This allows a step width of up to 0.000015259. If this is still not sufficient, the three colour channels can be arranged as $3 * 16$ bit. This allows 2^{48} possible output values. There are probably few applications where this kind of step width is necessary. Because all channels are used, the possible number of output variables of the Fuzzypic is reduced to one.

3 Applications with Fuzzypics

3.1 Sequences of Fuzzypics

A Fuzzypic alone is only capable of expressing two input values. This is not sufficient for most real life decision problems. In order to create a controller or decision system, Fuzzypics are aligned in sequences. The set-up of the output set O with it's possible output variables o_{red}, o_{green} and o_{blue} allows to distinguish up to three output values per Fuzzypic.

Depending on the usage of the colour channels, in a sequence a Fuzzypic is ancestor of up to three Fuzzypics. Let $X_{(I_A, I_B, O)}$ and $Y_{(I_A, I_B, O)}$ be two random Fuzzypics, then X and Y can be combined to a Fuzzypic $Z_{X,Y,O}$. Therefore the output variables of O_X and O_Y are used as the input values I_{Z_X} and I_{Z_Y} of Z. One necessary condition is

$$\forall o \in O_X : i \in I_{Z_X} \tag{37}$$

or $O \subseteq I_{Z_X}$ for X and likewise for Y. The condition that O_X can be a subset of I_{Z_X} allows the Fuzzypic Z to get the input from a other Fuzzypic Q, which meets the condition described in listing (37). This is possible, if Q and X have the characteristics of $X \leftrightarrow Q$ but as well O_Q and O_X can have the same semantic content but different ranges, what applies to the Fuzzypics SX and SQ.

Given that the input variable I_{Z_Y} is used for the successors $SX_{(I_X, I_{Z_Y}, O)}$ and $SQ_{(I_Q, I_{Z_Y}, O)}$ of both Fuzzypics X and Q. Let O_Q have the larger range than O_X. So we can write $SX \subset SQ$ with offset $I_X - I_Q$ what allows us to combine the two Fuzzypics into one Fuzzypic S.

3.2 Fuzzypic inference

To show the whole inference process with Fuzzypics, 'Figure 6' implements the example of the decision to go to the dentist or not. The model is extended by the situation of an planned journey abroad. So the modelled person has to account for the expected quality of the medical system abroad. If the quality is expected to be the same as at home $P(dentist)$ is not modified at all after processed by the left Fuzzypic. Else, the probability is altered.

The Fuzzypic on the left models the first relation between the parameters "Pain" and "Fear". The output set O is set to the probability $P(dentist)$ of going to the doctor. Where the Fuzzypic has the colour black, which represents the RGB vector $o = [0,0,0]$ and therefore the probability 0. The area where the Fuzzypic is white stands for the RGB vector $o = [255,255,255]$ with the probability 1. The shades of grey represent probabilities in between. In the example the set O uses 32 colour values for emphasize the Fuzzypic's structure of an array, so the value white matches the colour value 32. The second input value is the expected quality of the medial system abroad. The Fuzzypics has 21 columns, $[-10,10]$, negative for less quality positive for better quality. The column in the middle, where the quality has the value 0 stands for a neutral. This column is exactly the range of the 32 colours used. If it is hit, $P(dentist)$ is not altered.

Given that a person in a model has the variables "Fear" and "Pain" set to the values 5 and 18 the output value is white. Therefore the input for the next Fuzzypic is 32. Since this person plans to visit the dentist anyway, the probability $P(dentist)$ will stay at its maximum unless the expected quality abroad is better. This fact could reduce the probability to go to the doctor at home.

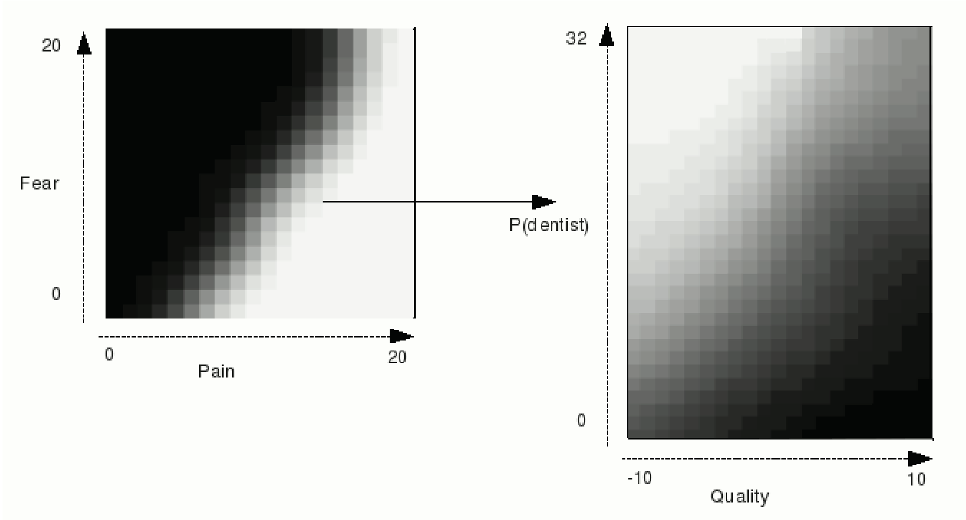

Figure 6: Sequence of Fuzzypics. The inference of the decision if a person visits the dentist

3.3 Fuzzypics for technical models

To show that Fuzzypics are not bound to problems of modelling human emotions, a simple exemplifying model of an overhead crane is expressed as a Fuzzypic. The example does not aim to give a working example but rather to express the basic connection between Fuzzypics and Fuzzy-Controls. 'Figure 7' shows a cargo crane as it is used for loading and unloading ships. The crane can only be moved gradually backward and forward. In between it has a neutral position. The red and blue colours stand for positive and negative values. White stands for neutral. The Fuzzypic includes the step of inference.

Let's apply I_A as value for "Distance" with a span $[20,100]$ as meters and I_B as value for "Drooping" with a span $[-30,30]$ with the unit degrees. A simplified Fuzzy-Control can model this set-up with the same values and few Fuzzy-Sets for each variable. As an appropriate output set 0 a variable "Movement of Joystick" with a relative scale $[-100,100]$ as percentage is adequate. Given that the method of inference and the method of Defuzzyfication are not changed throughout the life cycle of the Fuzzy-Control, the output value for a given pair of crisp, measured input values will be constant. For example the input values

$$I_{distance} = 90, ”toofar” \tag{38}$$

and

$$I_{drooping} = -20, ”left” \tag{39}$$

will result in a output value

$$O_{movement} = -90\%, ”high” \tag{40}$$

presumed that the rule base of the Fuzzy-Control contains a rule

$$”distance” = ”toofar” \cap ”drooping” = ”left” \rightarrow ”movement” = ”highnegative”. \tag{41}$$

The major characteristic of this kind of implementation is that the computer uses the Fuzzypic as a lookup table rather than using Fuzzyfication, Inference and Defuzzyfication for computing the decision. A simple lookup of a value in the storage, is a step of a few nano seconds.

3.4 Fuzzypics for documentation

The graphical representation of Fuzzypics is furthermore useful for easy and slim documentation of decision processes. If constant versions of Fuzzypics are used, e.g. in quality control and management, their decision values can be assigned traceable to products or decisions in quality control. Measured values can be assigned to Fuzzypics and processed through a sequence. The information needed for documentation is the identity of the Fuzzypic and its output value. Example is given in 'Figure 8'.

Fuzzypics can make an automated quality control comprehensible with their character of assigning visual representation to numbers. This improves the search for mistaken decisions and easy adjustment in the Fuzzypic sequence. Especially if a large number of products are to be tested, the speed of computation is an advantage where classical Fuzzy-Controls are regarded as too slow.

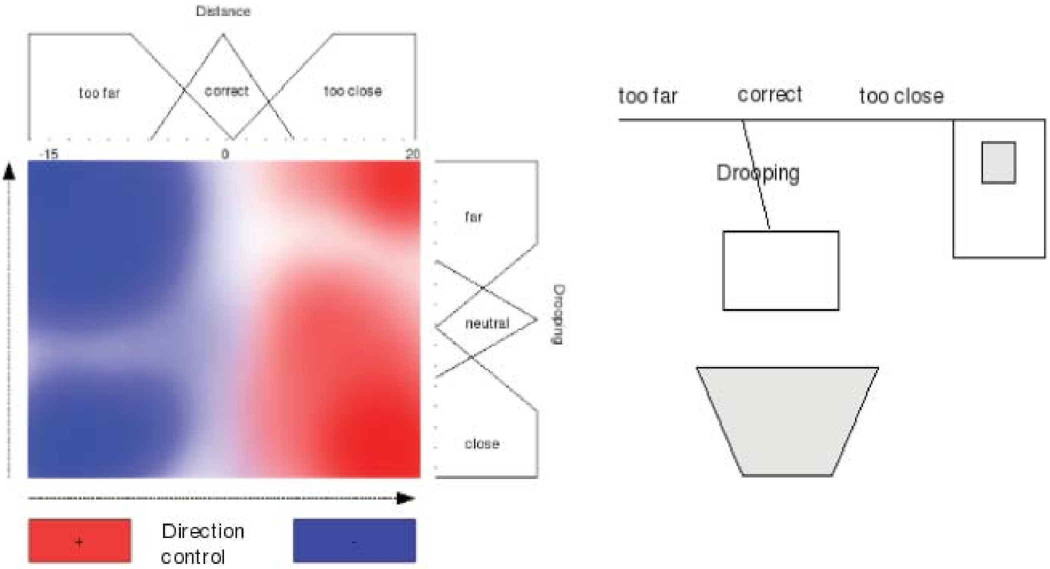

Figure 7: Fuzzypic in connection with Fuzzy-Sets, a schematic illustration of a simple Fuzzy-Controller for a crane.

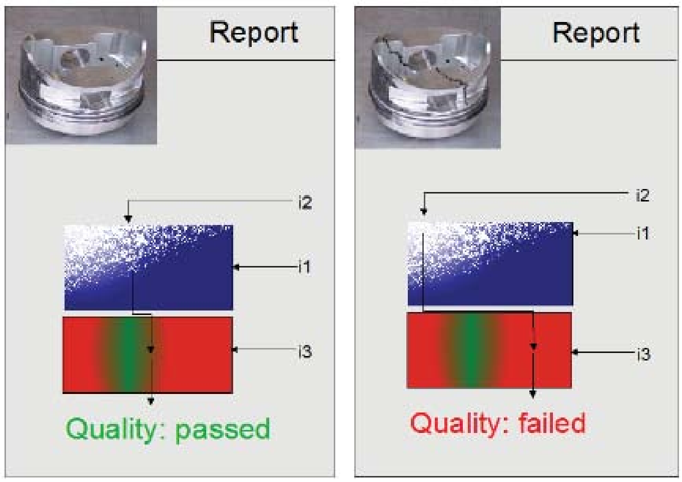

Figure 8: Documentation of quality control with included Fuzzypics

3.5 Problems

To create simple Fuzzypics standard Software can be used. For a more sophisticated applications of Fuzzypics, special software has to be written. Standard image editing tools do supply a wide range of algorithms for editing images. But for editing Fuzzypics sometimes content depending implementations of these algorithms are needed. Necessary is especially a well designed Graphical User Interface to uses this algorithms on the appropriate spot.

The second Fuzzypic in 'Figure 6' has the requirement that the middle column has to be the perfect colour gradient of the output set 0 from the Fuzzypic on the left. The areas to the left and the right of column have to meet specific requirements. E.g. on the left, the colour values must not be brighter than the colour value of the column at the specific line, on the right it must not be darker. Standard image processing tools do only provide limited tools to meet these restrictions successfully. For handling larger Fuzzypic sequences, modelling with many different files of Fuzzypics can be very difficult because the logic is only visible in the source code of the controller. Therefore an authoring tool will be useful to provide decent handling.

4 Conclusion

The main characteristics of Fuzzypics is that it is intuitively understandable due to human ability to easily perceive visual information and fast in computation, because instead of processing of a dozen of rules only one memory access on the lookup graphic is necessary. The concept could develop it strength at the point, where the use of

Fuzzy-Logic is too costly, too complex to implement or just too slow, but fuzzy handling of data is preferable. Furthermore a Fuzzypic must not be used in a sequence. It can easily be used to fuzzy single data sets of two input variables. Presently the concept of Fuzzypics is at an early stage. Further research has to be done as well as practical testing. The intrinsic characteristic of Fuzzypics to set two variables in relation can lead to an explosion of used images in a sequence. Combinations with common Fuzzy-Sets computation has to be regarded as a possible field of application. The concept understands itself as a high-speed add-on to the wide range of possibilities to model and compute vague data.

5 References

[1] Geyer-Schulz A.:. *Fuzzy Rule-Based Expert Systems and Genetic Machine Learning*, volume 3 of *Studies in Fuzziness*. Physica-Verlag, Heidelberg, 1995.

[2] Biewer B. *Fuzzy-Methoden: Praxisrelevante Rechenmodelle und Fuzzy-Programmiersprachen*. Springer Verlag, Berlin, Heidelberg, New York, 1997.

[3] Drechsel D.:. *Regelbasierte Interpolation und Fuzzy Control*. Friedr. Vieweg & Sohn Verlagsgesellschaft mbH, Braunschweig/Wiesbaden, 1996.

[4] Hearn D. and M. Baker:. *Computer graphics (2nd ed.)*. Prentice-Hall, Inc., Upper Saddle River, NJ, USA, 1994.

[5] Schumann H. and W. Mueller:. *Visualisierung, Grundlagen und allgemeine Methoden*. Springer, Berlin, Heidelberg, New York, 2000.

[6] Fischer J.:. Computation of fuzzy scenarios und decision problems by visualised fuzzypics. Oral presentation on 13. Bilateral Student Workshop CTU Prague - HTW Dresden, User Interfaces & Visualisation, 11 2008.

[7] Klir J. and B. Yuan:. *Fuzzy Sets and Fuzzy Logic: Theory and Applications*. Prentice Hall PTR, May 1995.

[8] Zadeh L. Fuzzy Sets. *In: Information Control*, Vol: 8:338–353, 1965.

[9] Zadeh L. Outline of a new approach to the analysis of complex systems and decision processes. *IEEE Trans. on Systems, Man, and Cybernetics*, SMC-3:28–44, 1973.

[10] El-Nasr M., J. Yen, and T. Ioerger. Flame-fuzzy logic adaptive model of emotions. *Autonomous Agents and Multi-Agent Systems*, 3(3):219–257, 2000.

[11] Esau N., L. Kleinjohann, and B. Kleinjohann:. An adaptable fuzzy emotion model for emotion recognition. In *Proceedings of the 4th Conference of the European Society for Fuzzy Logic and Technology (EUSFLAT-LFA 2005)*, Barcelona, Spain, 7 - 9 September 2005.

[12] Ghasem-Aghaee N. and T. Oeren:. Towards fuzzy agents with dynamic personality for human behaviour simulation. In *Proc of the 2003 Summer Simulation Conference, Montreal, PQ,Canada*, 2003.

[13] Zavodnik R. and H. Kopp:. *Graphische Datenverarbeitung, Grundzüge und Anwendungen*. Karl Hanser Vervag, München/Wien, 1995.

[14] Reimer U. *Einführung in die Wissensrepräsentation : Netzartige und schema-basierte Repräsentationsformate*. Teubner, Stuttgart, 1991.

[15] Bibel W., S. Hölldobler, and T. Schaub:. *Wissensrepräsentation und Inferenz*. Vieweg Verlag, Braunschweig, 1993.