A HIERARCHICAL FUZZY APPROACH TO TEMPORAL PATTERN RECOGNITION

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Abstract

In this contribution an approach for modelling and recognition of complex patterns in multivariate time series is being presented. Spatial, temporal and predicate logical elements are integrated into a model and may be built upon each other hierarchically. Integration of uncertainty and fuzziness as well as seamless interpretability are particularly emphasised. The focus of interest lies on the treatment of temporal expressions. For this purpose several options for describing and measuring the fulfilment of temporal requirements are introduced. Finally a novel generalised temporal measure emerges from these, offering a comprehensive parameterisable method to express temporal expectations. The classification of multivariate spatial information by means of the established Fuzzy Pattern methodology forms the basis of the model presented in this article. Temporal aspects can then be incorporated by analysing the development of fuzzy truth values over time. For the formulation of temporal requirements a so-called expectation function is introduced. In conjunction with a novel parameterisable measure which is employed to assess the expectations, this enables the model to describe a wealth of temporal expressions. The degree of fulfilment of a temporal expectation itself constitutes a new fuzzy truth value that evolves over time, therefore it can be processed likewise in subsequent steps. In this way, spatial and temporal elements of the model of a temporal pattern can be nested hierarchically. Since this approach relies on fuzzy truth values throughout the model, all elements can be arranged arbitrarily according to the requirements of the user, whilst maintaining interpretability and transparency. It is shown that verbal knowledge about a temporal pattern can be transformed to such a model in a straightforward way.

Keywords: Multivariate time series, temporal pattern recognition, fuzzy systems, decision support systems.

Presenting Author's Biography

Gernot Herbst received his diploma degree (Dipl.-Ing.) in Electrical Engineering from Chemnitz University of Technology in 2006. Afterwards he joined the faculty of Electrical Engineering at Chemnitz University of Technology, where he works as scientific research and lecturing assistant. His current research interests focus on the incorporation of fuzziness into the representation of time series and temporal phenomena.

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1 Introduction

How can a complex pattern in a multivariate time series be characterised? Let us therefor consider the properties of such a pattern. In technical or medical diagnosis, for instance, the development of diverse sensor values are being evaluated to detect important phenomena such as defects or diseases—provided that the manifestation of a phenomenon can be captured by sensors. When regarding diseases, our everyday experience tells us that they are typically being diagnosed from a combination and sequence of certain "events". Such an event often makes itself perceivable by specific measured values, and it runs through a distinctive temporal development. Differences within this temporal development can be decisive in distinguishing several diagnoses [1]. A complex diagnosis may now consist of a combination of these events, some of which *must* occur (in terms of a logical conjunction), some *may* occur (in terms of a logical disjunction), some in a certain sequence, some at arbitrary times. Partial diagnoses may furthermore be incorporated into more specific diagnoses which build on these.

To summarise, a pattern comprises spatial, temporal and predicate logical aspects that must be considered. Fig. 1 depicts a pattern consisting of three subpatterns (events). The temporal extent of these events must not be misinterpreted as sharply delimited, since the development of an event neither commences nor ceases suddenly in most realistic cases. Therefore a sharp description of the temporal relation e. g. by means of Allen's interval logic [2] appears unsuitable for practical applications. Especially for medical issues precise details are often inappropriate and infeasible [3]. In addition to the uncertainty of spatial information this must be taken into consideration when treating temporal information.

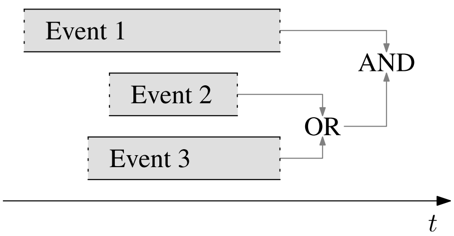

Fig. 1 Example of a compound temporal pattern

In this article an approach for the description of complex temporal patterns in multivariate time series will be introduced which combines spatial, temporal and logical elements. The uncertainty and fuzziness associated with each of these aspects shall explicitely be taken into account. It aims at building a system that may serve for on-line supervision or decision support purposes.

2 A model for temporal patterns

Many approaches to local pattern recognition in time series confine to spatial information. As soon as new information (measured data) becomes available, the data is being compared to all known patterns to deduce a diagnostic statement. If derived features are being used instead of the measured values, relatively complex patterns can be recognised by incorporating powerful signal processing techniques. But typically the temporal development of the patterns is not considered, albeit temporal aspects might implicitely be present within the features utilised.

A successful approach for describing multivariate patterns within this context is the method of *Fuzzy Pattern Classification* [4]. Besides the inherently multivariate mode of operation, its advantages include the possibility to incorporate fuzziness in the description of patterns as well as their compact, parametric representation. Fig. 2 shows this method's flow of information from measurements to classification results. Every set of measures—or optionally features—is assigned a fuzzy membership grade to each of all known patterns (classes). This corresponds to a transformation of a time series of sensor information $\boldsymbol{z}(t)$ or features $\boldsymbol{x}(t)$ to a time series of continuous membership values $\boldsymbol{\mu}(t)$. The diagnostic problem for phenomena would only be completed therewith if they underwent *no* characteristic temporal development.

The remaining part of this article shall be based upon the so-generated time series $\boldsymbol{\mu}(t)$ to include temporal and logical elements in the description of a pattern. $\boldsymbol{\mu}(t)$ already represents symbolic knowledge, *viz.* the degrees of fulfilment of the spatial requirements of all known patterns (events). The temporal progression of these truth values can now be evaluated independently of the scaling of the measurement data, as there now exists a time series normalised to $[0, 1]$. At this point it is already possible to describe logical relations between events using fuzzy operators. Hence two of the three requirements postulated in Section 1 are already implemented: the fuzzy treatment of spatial information and the use of predicate logic in a fuzzy manner as well.

For the formulation and verification of temporal requirements a combination of a so-called *expectation function* or *pattern* $e(\tau)$ and a comparison operation (as a measure for the fulfilment of an expectation) is being proposed in this article. The fundamental idea is to treat the course of a truth value μ—which can stem from spatial classification as well as logical operations—up to the current point in time t as a fuzzy set containing (potentially all) previous truth values. Their age shall be termed τ, such that $\mu(\tau = 0)$ corresponds to the most current information available. The fuzzy set is therefore sinistrally bounded by $\tau = 0$. At every point in time t a new set becomes available, hence it can be referred to as a *time dependent fuzzy set* [5] and shall be termed $\mu(t, \tau)$. An exemplary set ist shown in Fig. 3.

The expectation function $e(\tau)$ forms a fuzzy set as well and can, for instance, be interpreted as a temporal frame for the occurance of an event (cf. Fig. 5). Sections 3 and 4 will be dealing with different interpretations of the expectation pattern and provide measures for the fulfilment of the respective temporal expectation. At this time it is important to know that this will result in continuous truth values as well. So all requirements

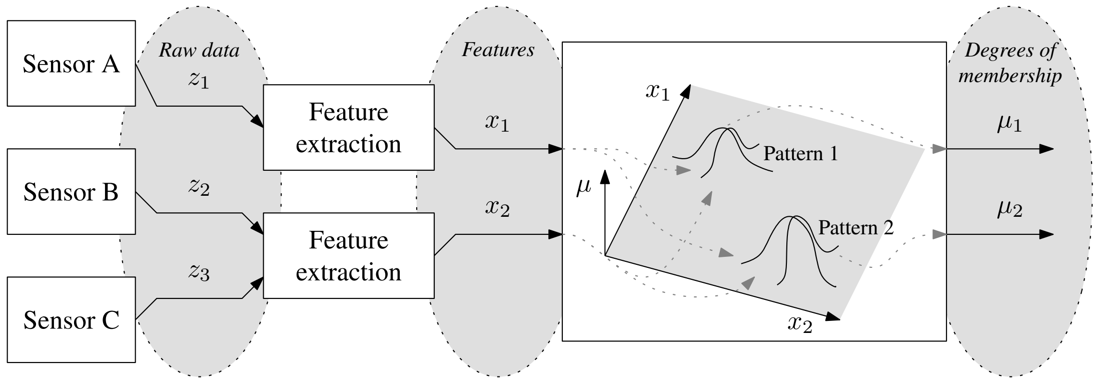

Fig. 2 Information flow from raw sensor data to features and their fuzzy classification (example with two classes in a two-dimensional feature space)

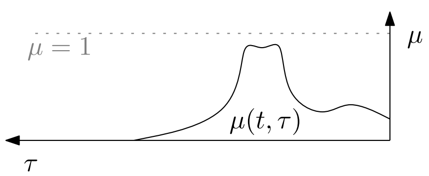

Fig. 3 Example of the temporal development of an event $\mu(t, \tau)$. Note that the τ axis is displayed mirroredly. Since τ represents the age of the truth values, the course from left to right portraits the temporal development up to time t that way.

of a pattern—spatial, temporal and logical—will be assessed by fuzzy truth values at each point in time, thus forming time series of their own. Since temporal and logical expressions are both based on courses of truth values here, they can be arranged and nested in a hierarchy, forming a representation of a complex temporal pattern.

An exemplary information flow employing truth values of different symbolic meaning can be found in Fig. 4. Two membership values, that could, for instance, stem from a spatial classification according to Fig. 2, are firstly compared to different temporal expectations. Afterwards, these degrees of fulfilment are being logically combined to the total degree of fulfilment of this temporal pattern. The result can lateron be processed by subsequent temporal or logical operations.

One important feature of the model presented here is that truth values are being used throughout as soon as measurement values have been transformed to membership grades by means of fuzzy spatial classification. These truth values can equally well represent expert opinions. In contrast to traditional decision support systems, experts may not only use the information presented at the output of the system, but just as well bring in their knowledge as additional *input* during online operation. Thus information which is not or hardly measurable can be integrated and processed, too.

3 Comparison of temporal expectations and the actual manifestation

As already mentioned in Section 2, the expectation function $e(\tau)$ may adopt different meanings in the formulation of temporal expectations. The differentiation takes place in the manner of comparing the truth values $\mu(t, \tau)$ of an actual event with $e(\tau)$. Three distinctive interpretations have to be considered and will be described in the following.

3.1 $e(\tau)$ as temporal frame

In this case, the expectation function $e(\tau)$ acts as an unsharp *time frame* for the occurrence of an event. Depending on the dimensioning of this frame there are still many degrees of freedom for the actual manifestation of an event. Of prime importance is *that* an event takes place, not *how* or when exactly. There are no requirements regarding the persistence of an event—as long as it remains within the time frame.

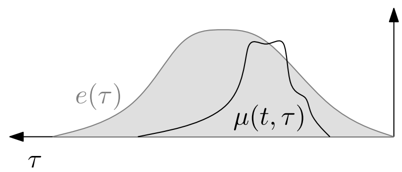

Fig. 5 Exemplary event according to Section 3.1. It almost completely occurs within the fuzzy time frame $e(\tau)$ (plotted in grey).

As stated before, an event typically does not occur instantly, but rather develops within a certain period of time (as in Fig. 3) with possibly fuzzy boundaries. Thus for the assessment of an event, it appears necessary to consider its complete course of truth values $\mu(t, \tau)$ (compare Fig. 5). As a measure of fulfilment of the expectation "event occurs within $e(\tau)$", we therefore propose the object-based covering ratio [6] as shown in Eq. 1. This conforms to a classification of a dispersed fuzzy object $\mu(t, \tau)$ when $e(\tau)$ is being treated as the corresponding class. It is important to note this similarity in the assessment of temporal and spatial requirements by means of fuzzy classification.

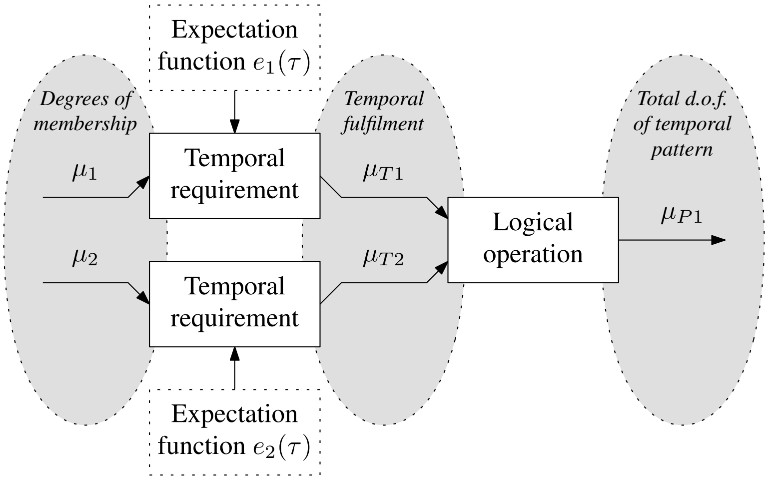

Fig. 4 Information flow from membership degrees to the total degree of fulfilment of one temporal pattern

$$dof_1 = \frac{\int \cap(e(\tau), \mu(t,\tau))\, d\tau}{\int \mu(t,\tau)\, d\tau} \tag{1}$$

If an event shifts away from the core area of temporal attention, this will result in a floating transition from fulfilment to non-fulfilment of the respective temporal expectation. As demanded in Section 2, the presented measure of fulfilment provides a continuous truth value therewith. This truth value again represents a new, higher-level symbolic meaning, but keeps signal character [7]. The underlying temporal information about a developing process is therefore preserved and may be furthermore evaluated in subsequent steps.

3.2 $e(\tau)$ as reference run

A different interpretation arises if $e(\tau)$ is being treated as a *reference run* for the truth values of $\mu(t,\tau)$, therefore posing very distinct requirements upon the development of an event. $e(\tau)$ might represent a prototypic course gained from a learning process.

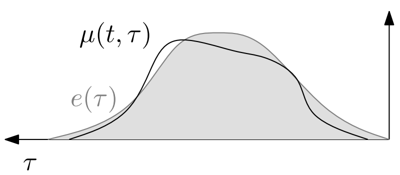

Fig. 6 Example of an event according to Section 3.2. $e(\tau)$ acts as reference run that is being reproduced by the actual event relatively well.

The persistence of the event is now determined by $e(\tau)$ and leaves no degree of freedom, contrary to the case of Section 3.1. Any deviation from the reference run should diminish the degree of fulfilment of this temporal expectation. Thus a similarity measure has to be used as measure of fulfilment now. Here, the generalised covering ration of μ and e (Eq. 2) will be proposed. It is a fuzzy measure and tightly related to Eq. 1. This relation will be taken advantage of lateron.

$$dof_2 = \frac{\int \cap(e(\tau), \mu(t,\tau))\, d\tau}{\int \cup(e(\tau), \mu(t,\tau))\, d\tau} \tag{2}$$

3.3 $e(\tau)$ as minimum run

A third interpretation finally arises when the persistence of $e(\tau)$ is to be surpassed by an event. Hence $e(\tau)$ acts as a *minimum run* for the truth values of $\mu(t,\tau)$. Thus $e(\tau)$ could also be looked at as a testing window during which the continuous occurrence of the event is being required (Fig. 7).

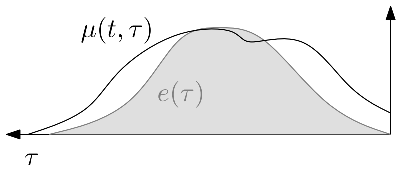

Fig. 7 Exemplary event for Section 3.3. $e(\tau)$ acts as testing window for its persistence. The event μ depicted here fulfils these requirements almost completely.

Comparing to case 1 (Section 3.1) one might note that it is now $e(\tau)$ which has to be contained in $\mu(t,\tau)$. μ and e can be said to have changed their roles. Analogously to dof_1 we now propose an object-based covering ratio as measure of fulfilment which is—contrary to dof_1—applied to e as an object (cf. Eq. 3). A similar measure is also used by [8] to assess the partial fulfilment of a temporal expectation. dof_3 and dof_1 form opposite measures based on oppositional expectations regarding the persistence of an event.

$$dof_3 = \frac{\int \cap(e(\tau), \mu(t,\tau))\, d\tau}{\int e(\tau)\, d\tau} \tag{3}$$

3.4 Discussion

A trivial measure of fulfilment

All interpretations dealt with in Sections 3.1–3.3 regard an event characterised by its temporal development. A trivial fourth case emerges if only *one* truth value of $\mu(t, \tau)$ is being used to assess the occurrence of an event, that is if—in an optimistic manner—only the best possible realisation of μ within the window e is considered, as can be seen from Eq. 4. This nonpersistent measure is, for instance, used by [8, 9].

$$dof_4 = \sup \cap (e(\tau), \mu(t, \tau)) \tag{4}$$

Apart from the questionable optimism expressed by Eq. 4, it makes a system susceptible to possible faults in the precedent decision process. If an invalid truth value occurs due to an erroneous measurement, it might be just this value which is used by Eq. 4 to decide on the fulfilment of an temporal expectation. All of the other measures offered here exhibit a more compensatory behaviour towards singular errors.

Additionally, dof_4 does not guarantee that an event mainly takes place *within* a given time frame. In contrast to this, dof_1 penalises events that widely occur outside of $e(\tau)$ by means of normalisation to $\int \mu(t, \tau)\, d\tau$.

Modification of dof_1

On closer inspection, the μ-based covering ratio in Eq. 1 exhibits the following property: If an event described by $\mu(t, \tau)$ occurs completely within the window given by $e(\tau)$, the measure might opt for total fulfilment of the expectation even if the event's maximum realisation is $\sup \mu(t, \tau) < 1$. This depends upon $e(\tau)$ and the T-norm chosen and might be an undesirable behaviour for some applications.

To avoid this, the maximum truth value could be included in the decision, for instance by normalising the fuzzy set $\mu(t, \tau)$ (as done in Eq. 5). This corresponds to a conjunction of the maximum spatial degree of fulfilment given by the precedent decision and the temporal degree of fulfilment by means of a product operator.

$$dof_{1m} = \frac{\int \cap (e(\tau), \mu(t, \tau))\, d\tau}{\int \mu(t, \tau)\, d\tau / \sup \mu(t, \tau)} \tag{5}$$

However, this affects the robustness of the decision regarding singular preceeding errors (outliers in the course of μ) analogously to the measure in Eq. 4. In this case, smoothing and filtering steps should be introduced to encounter the data with an appropriate degree of mistrust, so that errors cannot affect the decision process as a whole.

Chosing T- and S-norms

Up to now, the set operations (T- and S-norms) used in the measures dof_i have not been elaborated on. They are a degree of freedom for the user, who has to consider their respective behaviour nonetheless. Especially in dof_1 (Eq. 1) and dof_3 (Eq. 3) the use of interactive fuzzy operators beyond the commonly used $\min$ und $\max$ can be beneficial due to the consideration of both sets' fuzziness.

On the other hand, when employing $e(\tau)$ as reference run (accordingly using dof_2), two identical fuzzy sets can only lead to a degree of fulfilment $dof_2 = 1$ if the operations involved are idempotent. In that case, $\min$ and $\max$ would therefore constitute an appropriate choice. Otherwise one would have to consider that even lower truth values might already represent a higher degree of fulfilment.

4 On the expectation function

In Section 3 the threefold interpretation of the expectation function $e(\tau)$ was introduced. This results from the way in which the time dependent fuzzy set $\mu(t, \tau)$—describing the manifestation of an event—and $e(\tau)$—describing an expectation—are set into relation by different measures for the degree of fulfilment. In each case, $e(\tau)$ represents a fuzzy description of a time point or interval, as used by Dubois and Prade in their temporal logic [10]. The difference here is that the domain is not the absolute time but rather the age τ which is defined relatively to the current point in time t. Furthermore the precise meaning of $e(\tau)$ is determined only in conjunction with one of the introduced measures dof_{1-3}.

For different classes of expectation functions, these distinctive features can, amongst others, be found: representation, normalisation, symmetry and support; some of which shall be discussed in the following.

Parametric vs. nonparametric representation

In the process of formulation of a temporal requirement by an expert it is beneficial if the expectation pattern can be expressed by few interpretable parameters, as found in trapezoidal or potential functions. On the other hand, a nonparametric representation can be more suitable if $e(\tau)$ is being used as a reference run (using dof_2), for instance if it was gained experimentally from a learning process.

Normalisation

Generally speaking $e(\tau)$ maps $[0, \infty)$ to the interval of truth values $[0, 1]$. However, if the fuzzy set $e(\tau)$ is not normalised and its core therefore empty, the difference $1 - \sup e(\tau)$ can be viewed as a measure of uncertainty if the respective event shall occur at all [10]. In the case of dof_1, where $e(\tau)$ represents a time frame, a normalisation appears advisable. If $e(\tau)$, on the other hand, depicts a minimum realisation of an event (dof_3), an expectation function with $\sup e(\tau) < 1$ can express less strict requirements regarding the occurrence of an event.

Infinite support

At first glance, the infinite support of $e(\tau)$ appears problematic when regarding a practical implementation. A consequence of infinite cardinality is that all available information gathered up to the current point in time t would influence a decision about correspondence of temporal expectation and realisation. Thus a restriction to a maximum age $\tau_{\max}$ of the information considered is both necessary and also well interpretable: For dof_1 and dof_2 it determines the temporal distance that an event can repeat itself with. $\tau_{\max}$ has not necessarily to be defined by an expert, but can be automatically determined at least if $e(\tau)$ is convex. In that case it should be chosen so that $e(\tau_{\max})$ has sufficiently diminished to a near-zero value.

When using fuzzy sets with finite support, such as triangular or trapezoidal functions, this problem is bypassed a priori. But note that it can be difficult for experts to specify crisp boundaries nonetheless, especially when modelling unsharp phenomena [11].

5 A generalised measure of temporal fulfilment

From a crisp point of view, the three cases presented in Section 3 appear sufficient to describe all possible relations between a temporal expectation and an actual event, though each of the measures itself is a fuzzy measure, of course. But beyond this one can think of in-between cases, for instance if not an exact match of μ and e is required (as with dof_2), but an a shorter realisation of an event would suffice as well. In this example both dof_1 and dof_2 would be appropriate to a certain extent. Therefrom arises a need for measures to flexibly assess all conceivable requirements regarding the persistence of an event that range between the salient cases presented in Sections 3.1–3.3. In what follows a generalised measure covering these problems will be deduced from the present three measures dof_{1-3}.

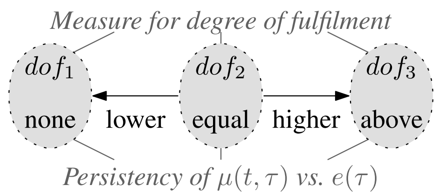

Fig. 8 Persistence of an event required by the individual measures

Firstly it must be clarified which of these cases may superimpose each other. When considering Eqs. 1–3, the persistence of an event required by these measures increases in each case (compare Fig. 8). Thus it would be sufficient to allow nuances between two adjacent measures, respectively, that is between dof_1 and dof_2 on the one hand and between dof_2 and dof_3 otherwise. In contrast, dof_1 und dof_3 mutually exclude each other, since a lower and higher persistence cannot be demanded simultaneously.

The generalised measure of fulfilment shall therefore be parameterisable with a weighting factor that can be adjusted to all nuances between three distintive settings. Therefore a parameter $\gamma \in [-1, 1]$ is now introduced so that the three required settings (as well as all graduations in between) can be reached according to Eq. 6.

$$\gamma = \begin{cases} -1 & \text{case 1, } \mu(t,\tau) \text{ within } e(\tau) \\ 0 & \text{case 2, } \mu(t,\tau) \text{ matches } e(\tau) \\ 1 & \text{case 3, } \mu(t,\tau) \text{ outlasts } e(\tau) \end{cases} \tag{6}$$

When comparing the formulae for the individual degrees of temporal fulfilment (Eqs. 1, 2, 3 or Eqs. 5, 2, 3 when using the modified measure dof_{1m}), the difference is only being reflected in the respective reference area in the denominator. The idea is now to utilise this strong relationship between the measures and employ the parameter γ to implement a combination of the integrands. In the medial setting of γ, the union of both sets μ and e is demanded, whereas for the outer parameter settings $\gamma \to \pm 1$ the integrand has to be merged in the respective individual sets. This can be achieved by a bidirectionally parameterisible union operator specifically designed to meet these demands. Such an operator $\cup_\gamma$ is proposed in Eq. 7. For $\gamma = 0$ this operator exhibits S-norm character. The S-norm employed there can still be chosen freely according to the requirements of the user and the remarks of Section 3.4. For $\gamma \to \pm 1$ the properties of an S-norm (particularly commutativity) do not hold, however, since $\cup_\gamma$ returns the individual sets then.

$$\begin{aligned} \cup_\gamma(\mu_A(x), \mu_B(x)) = (1 - |\gamma|) \cdot \cup(\mu_A(x), \mu_B(x) \\ - \min(\gamma, 0) \cdot \mu_A(x) \\ + \max(\gamma, 0) \cdot \mu_B(x) \end{aligned} \tag{7}$$

The generalised parameterisable measure for the fulfilment of temporal expectations can now be expressed in a very compact manner (Eq. 8). The detailed formulation can be found in Eq. 9. If the modified measure dof_{1m} according to Eq. 5 is to be incorporated into the generalised measure, $\cup_\gamma$ merely has to be adapted in a way that it returns a normalised set μ for $\gamma \to -1$. Eq. 10 shows the modified generalised measure for this case in detailed notation.

$$dof = \frac{\int \cap(e(\tau), \mu(t,\tau)) \, d\tau}{\int \cup_\gamma(e(\tau), \mu(t,\tau)) \, d\tau} \tag{8}$$

The effect of the parameterisable union operator $\cup_\gamma$ for all settings of $\gamma \in [-1, 1]$ is illustrated in Fig. 9 exemplarily for two fuzzy sets defined on a domain of τ. In this figure $\cup_\gamma$ was chosen to be based on the Hamacher sum (as an example of an interactive operator), which defines the character of the union for $\gamma \approx 0$. The unifying behaviour can be spotted in Fig. 9 as well as the two individual fuzzy sets delivered for the outer settings of γ.

The advantage of this generalised measure for assessing the degree of fulfilment is firstly that all requirements

$$dof = \frac{\int \cap(e(\tau), \mu(t,\tau))\, d\tau}{\int \left[(1-|\gamma|)\cdot \cup(e(\tau),\mu(t,\tau)) - \min(\gamma,0)\cdot \mu(t,\tau) + \max(\gamma,0)\cdot e(\tau)\right]\, d\tau} \tag{9}$$

$$dof_m = \frac{\int \cap(e(\tau), \mu(t,\tau))\, d\tau}{\int \left[(1-|\gamma|)\cdot \cup(e(\tau),\mu(t,\tau)) - \min(\gamma,0)\cdot \mu(t,\tau)/\sup \mu(t,\tau) + \max(\gamma,0)\cdot e(\tau)\right]\, d\tau} \tag{10}$$

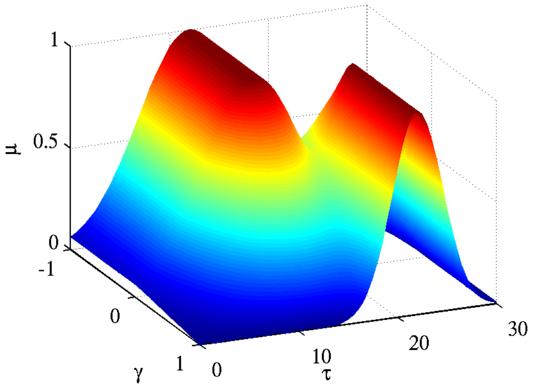

Fig. 9 Results of the parameterisable union operator (Eq. 7) applied to two exemplary fuzzy sets defined over the domain of τ for all possible settings of γ

regarding the persistence of an event can be gradually expressed and evaluated. The three interpretations and measures of Section 3 are explicitely contained herein. Secondly, when a description of a temporal expectation is being formulated (e. g. by an expert), it is no longer necessary to select a particular measure for its fulfilment, but merely sufficient to specify one single parameter. In conjunction with the expectation function $e(\tau)$, this parameter delivers the whole range of temporal expressiveness dealt with in this article.

6 Case study: a tropical disease

In this section the proposed methodology shall be employed to model a (purely fictional) tropical disease. This model could then be used for automatic or supportive diagnosis of the disease. It will be shown that the process of transforming verbal temporal knowledge into an hierarchical fuzzy model is transparent and easily comprehensible. The fictional disease shall exhibit the following symptoms: "Two or three months after a visit in a tropical country, the patient suffers from high temperatures. Additionally, diarrhoea occurs for a period of at least three days within two weeks before the fever appears."

As can be seen, the diagnosis comprises three aspects: the fact of having visited a tropical country a certain while ago, the occurrence of diarrhoea with a specific temporal profile, and lastly the appearance of fever. All three facts resp. symptoms shall be described by fuzzy or crisp truth values: $\mu_v(t)$ contains the information about the patient's travels into tropical regions. It is nonzero for times when the patient visited such a country. $\mu_f(t)$ reports the temporal development of the patient's temperature such that $\mu_f \rightarrow 1$ describes fever, and $\mu_f \rightarrow 0$ normal temperature. μ_f might stem from a fuzzy classification of measured temperature values or from verbal description of the patient himself. Finally, $\mu_d(t)$ contains the information about the occurrence of diarrhoea, and will typically be given verbally by the patient as well. Its fuzzy truth value may express the severeness of this symptom. The temporal model of the disease is being depicted in Fig. 10.

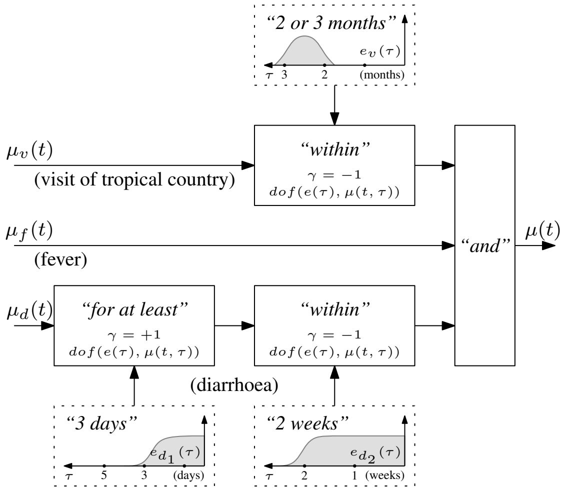

Fig. 10 A fuzzy temporal model for a fictional tropical disease

For $\mu_v(t)$, an expectation function $e_v(\tau)$ was defined which acts as a temporal frame where the patient's travel to a tropical country is expected to happen within. The actual (mathematical) definition of $e_v(\tau)$ will be omitted here for brevity, but it can be seen from Fig. 11 that it matches the verbal expression "two or three months ago". It represents the incubation period of this disease, therefore its membership values peak around an interval of two to three months on the temporal axis τ. The fulfilment of this temporal expectation will be verified by dof, the generalised measure introduced in Eq. 9. As $e_v(\tau)$ shall act as temporal frame, $\gamma = -1$ must be used here as the parameter of dof (cf. Eq. 6).

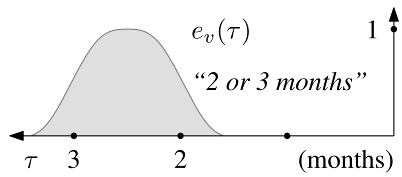

Fig. 11 Expectation function $e_v(\tau)$: a fuzzy set representing the incubation period of the disease

The temporal development of $\mu_d(t)$ must be treated twice, as there are two different temporal aspects: Firstly, this symptom (diarrhoea) shall last for at least three days (cf. the first expectation function e_{d_1} in Fig. 10), and this in turn is being expected to happen somewhen in a time frame of two weeks (cf. e_{d_2}). Thus e_{d_1} acts as a minimum run for $\mu_d(t)$ (therefore dof must be employed using $\gamma = 1$), and the fulfilment of this first expectation shall occur within a time frame defined by e_{d_2} (so dof must be used with $\gamma = -1$). Finally, the temporal fulfilment of the developments of μ_v and μ_d are being combined with μ_f by a fuzzy T-norm operator, thus forming the truth value μ of this disease's diagnosis.

When comparing the verbal description of the disease with the model of Fig. 10, all elements can be easily recognised. Furthermore, the verbal description can be derived back again from the model without effort.

7 Conclusion

After discussing the different aspects of a complex temporal pattern, a method for modelling and recognition of patterns in multivariate time series was introduced in this article. Spatial, temporal and logical requirements and relations can be described in a simple and comprehensible manner. The representation and processing of all aspects of a temporal pattern are interpretable and transparent throughout the model. Therefore it qualifies [12] for an application as diagnostic or decision support system.

The idea of the expectation function $e(\tau)$ and its threefold interpretation was introduced, and likewise a measure for assessing the fulfilment of each of these temporal expectations given. Finally a new generalised parameterisable measure was deduced from these, which both offers new possibilities in temporal description and simplifies the design process as well.

The fulfilment of spatial, temporal and logical expectations is being described by means of fuzzy truth values. Although each new truth value represents a higher-level symbolic meaning, it always retains signal character. Since the processing of temporal and logical knowledge is based on these courses of truth values and does not operate on measurement signal level, temporal and logical requirements can be nested hierarchically and build upon each other to reflect complex patterns. Furthermore, expert opinions can be incorporated as additional inputs of the decision process.

A subset of the functionality described here has already been used in the situation recognition module of an autonomous mobile system [13]. Other areas of application for the methodology introduced here include intelligent data analysis, e. g. for medical systems, where efficient and interpretable decision support systems are increasingly required [12, 14]. In the field of technical diagnosis, more sophisticated methods are called for as well [15], so this would be another area of application, especially since the rapprochement of technical and medical diagnostic methods seems appropriate [16]. The approach presented here recommends itself through its seamless interpretability and the fact that modelling of temporal patterns has not necessarily to be conducted by knowledge engineers [17], but can therefore be accomplished by experts of the application area as well.

8 References

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