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A fuzzy case-based system for weather prediction

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Case-based reasoning is emerging as a leading methodology for the application of artificial intelligence. We describe an investigation into the application of case-based reasoning in airport weather forecasting. Knowledge about temporal features that human forecasters use to construct analogous climatological scenarios is encoded in a fuzzy similarity measure. The fuzzy similarity measure is used to locate the k-nearest neighbours from the historical database. These nearest neighbours are in turn adapted to produce values for the forecast parameters. Five sets of experiments show inter alia that the proposed WIND-1 system produces highly accurate forecasts based on real climatological data, using a standard technique for assessing the accuracy of forecasts produced by human forecasters.

Keywords: case-based reasoning, weather forecasting, fuzzy similarity measure

1. OVERVIEW

Weather forecasting is a complex process that involves numerous specialized fields of expertise. The output from computationally intensive numerical weather prediction (NWP) models forms the starting point of the forecasting process. Expert forecasters have both a general knowledge of large-scale weather systems and specific knowledge about the idiosyncratic behavior of local scale weather phenomena. These expert forecasters, in effect, bridge the gap on the local scale between simple persistence forecasting and the output from the NWP models [1]. The types of forecasts commonly made by expert forecasters include terminal aerodrome forecasts (TAFs), public forecasts and marine forecasts. In addition to these, many specialized forecasts are produced for power companies, oilrigs and others. Because much of the knowledge and expertise used by weather forecasters is analogical the possibility of augmenting the forecasters experience with the detailed knowledge of similar weather situations from several prior decades of recorded weather data seems most promising. This is the possibility offered by applying case-based reasoning techniques to the problem of weather forecasting.

Recently intelligent systems (IS) using artificial intelligence (AI) techniques have been used to forecast visibility, marine fog, precipitation, severe weather and other climatological conditions [e.g., 2, 3, 4, 5]. The IS modeling approach is complementary to NWP modeling that uses computationally intensive dynamical, thermodynamical and statistical algorithms to produce large scale (hemispherical) static forecasts. These large-scale static forecasts are not sufficiently stable on a small scale where local effects and recency become significant or even predominant. The larger scale numerical models can be scaled down by using more detailed numerical models that take the output from the large-scale models and also include local effects and the most recent data from weather stations in the immediate area. The smaller-scale numerical models are not intuitive, need consistent and complete data and may be difficult to apply in real time. On the other hand, using IS to model smaller scale climatology has many of the characteristic advantages that typically arise when AI techniques are applied. For example, the resulting climatological models are intuitive because the models are constructed from human experts using knowledge acquisition techniques. Like the human experts themselves, these models can cope with uncertainty, incompleteness and recency and generally are not computationally intensive. In addition to this, CBR models are inherently analogical are thus possibly the most intuitive of all IS models particularly when applied to problem situations, such as analogue forecasting, in which reasoning is predominantly analogical.

The WIND project [6], which began in 1997, addresses the problem of forecasting horizontal visibility and cloud ceiling heights at airport terminals through the application of CBR that uses a fuzzy similarity metric with built in climatological knowledge. The case-based system retrieves stored cases from the historical database using a k-nearest neighbour retrieval mechanism based on the fuzzy similarity metric. Each retrieved case represents a previously encountered climatological situation that is similar to the current situation. The retrieved cases are adapted to construct a forecast scenario. The implemented system (WIND-1) is extensively tested using standard meteorological quality control statistics [7] on the available historical data (1961-1996).

This paper first describes the problem of terminal aerodrome forecasting and persistence climatology. Secondly it presents a summary of pertinent aspects of case-based reasoners. Thirdly it describes details of the WIND-1 system itself. Fourthly we describe the experimental testing of the system and inter alia the quality of the forecasts produced by WIND-1. We close with a discussion of the lessons learned from the project and future work.

2. TERMINAL AERODROME FORECASTING

The atmosphere is in a state of constant change driven globally by solar energy and by energy derived from the rotation of the earth. Latitude, ocean currents and landmasses determine weather features on a global scale. NWP models take as input readings from weather stations, weather buoys, satellite images, atmospheric probes and other sources. These values serve as initial conditions to systems of equations that describe the atmosphere. The models are run statically and produce forecasts on a six hourly basis that serves as the foundation of all forecasts. Output from these models is useful for large scale and longer-term forecasts. However, the complete description of the atmosphere in this form is far beyond current capability of such models, in part because the accuracy of the models is inherently dependent upon the initial conditions that are inherently incomplete, i.e., the systems are chaotic.

For fine grain forecasting, knowledge of the climate of the immediate region is used by forecasters and the technique is known as climatological forecasting, according to Huschke [8]. Huschke further defines a "persistence forecast" as "a forecast that the future weather conditions will be the same as the present conditions." Thus persistence climatology (PC) bases predictions for the present case on the outcomes of similar past cases. To emphasize, persistence climatology is an inherently analogical method of weather forecasting based on similar past weather situations. Persistence climatology is widely recognized as a formidable benchmark for very-short-range prediction of ceiling and visibility, which are critical attributes of TAF's [9]. PC is used as the basis of various refinements that use weather records and observational data from surrounding stations to define weather categories that are used for forecasting [9,10].

Of all types of forecast TAFs are required to be most precise both in terms of measurable weather conditions and in terms of timing. TAF forecasts of the height of low cloud ceiling are expected to be accurate to within 100 feet; forecasts of the horizontal visibility on the ground, when there is dense obstruction to visibility, such as fog or snow, are expected to be accurate to within 400 metres; and forecasts of the time of change from one flying category to another are expected to be accurate to within one hour. In contrast public and marine forecasts can be much less precise. In public forecasts, for example, it may be sufficient to predict "variable cloudiness this morning," and in marine forecasts, it may be sufficient to predict "fog patches forming this afternoon."

When ceiling and visibility at a busy airport are low, in order to maximize safety, the rate of planes landing is reduced. When ceiling and visibility at a destination airport are forecast to be low at a flight's scheduled arrival time, its departure may be delayed in order to minimize traffic congestion and related costs. An examination of the causes and effects of flight delays at the three main airports serving New York City concluded that a correctly forecast timing of a ceiling and visibility event (i.e., a significant change) could be expected to result in a savings of approximately $480,000 per event at La Guardia Airport [11]. Based on a related study, the U.S. National Weather Service estimated that a 30 minute lead-time for identifying cloud ceiling or visibility events could reduce the number of weather-related delays by 20 to 35 percent and that this could save between $500 million to $875 million annually [12].

A goal of our research is to enable an improvement in the quality of TAFs in terms of accuracy and timeliness. Persistence climatology is clearly an important technique used in the production of short-term forecasts, including TAFs. It is in essence analogical or case-based and uses detailed knowledge of local historical conditions and more recent readings from local weather stations and other sources to bridge the gap between the hemispherical scale of the NWP models and the details required by local users. We therefore propose that the strengths and abilities of CBR complement the techniques currently used in persistent climatology and can be used to improve the accuracy of short-term forecasts. In the following sections we focus on the production of short-term TAFs.

3. CASE-BASED REASONERS

Case-based reasoning [13] has been used to solve problems in diverse areas including decision support, help desk support, product cataloguing and maintenance support [14, 15]. In order to solve a current problem a case-based reasoner requires a library of past problems and the solutions that were used to solve the past problems. The case-based reasoner works by using a measure of similarity to retrieve past problems that are most similar to the current problem. The reasoner then combines and adapts the solutions to the most similar past problems to generate a proposed best solution to the current problem. Clearly the designs of the similarity metric and the adaptation algorithm are crucial to the functionality of any case-based reasoner. Existing case-based reasoners differ widely in the design of these two component mechanisms.

Similarity metrics used in case-based reasoners for retrieval vary greatly. Euclidean norms and Hamming distances are the most common; rule-based metrics have been discussed [16]; some metrics use domain knowledge [17]; similarity measures have been adapted to use fuzzy set based formalisms [18] and others use hybrid fuzzy measures [19]. Our similarity measure most closely resembles those of [18] and may best be described as a hybrid fuzzy measure with thresholds that exploit domain based knowledge elements. For retrieval we use a k-nearest neighbour algorithm [20] with the similarity metric.

Forgetting mechanisms [13] are used in many case-based systems to help control the amount of memory used by the case library. In our proposed system forgetting is achieved by the use of recency in the similarity algorithm while experiments on the case library suggest that the size of the library may be reduced by removing older cases up to a point without adversely affecting the accuracy of the forecasts produced by the system.

During the problem-solving process, a number of similar solutions are retrieved not one of which is completely valid. The retrieved solutions need to be adapted to arrive at a valid solution to the current problem. Adaptation mechanisms are often user-driven and can be rule-based or rely on generalization and refinement heuristics [21]. Adaptation mechanisms have been categorized as compositional or transformational [22]. Compositional adaptation occurs when knowledge is used to combine portions of approximate solutions to achieve the desired solution. Transformational adaptation occurs when more comprehensive knowledge needs to be used to add extra components to the retrieved solutions to achieve a satisfactory result. In WIND-1 we propose a smoothing adaptation mechanism that is supplemented with knowledge of weather scenarios and case recency.

4. FUZZY METHODOLOGY FOR TEMPORAL CASES

Airport weather observations (METAR's) are routinely made at all major airports in real time on an hourly basis. A new set of observations is added to the database each hour and hence a new problem case is also generated each hour. In this research we used an archive of 315,576 consecutive hourly airport weather observations made at Halifax International Airport (CYHZ, located at 44º53'N 63º30'W) during the 36-year period from 1961 to 1996.

4.1 Definitional case structure

Let $a(t) = (a_0(t), a_1(t), a_m(t))$ represent a set of m attributes observed at one time t. In Table 1, each row contains one hourly observation made at time t, and each observation contains m = 12 attributes (attributes are grouped into 10 columns, but temporal attributes include time of year and time of day, and weather attributes include precipitation type and intensity, for a total of 12).

A case to predict for is a series of 13 consecutive sets of

Table 1 Consecutive hourly observations for Halifax Airport. (Note 1 Meaning of weather tokens: ZR- is light freezing rain, F is mist, and R- is light rain.)

Y/M/D/H	Ceiling 30's m	Horizon Visby. Km	Wind Dir x10 deg	Wind Speed km/h	Dry Bulb deg C	Dew Point deg C	MSL Press. kPa	Cloud Amt. tenths	Weather [1]
64/1/2/0	15	24.1	14	16	-4.4	-5.6	101.07	10	
64/1/2/1	13	6.1	14	26	-2.2	-2.8	100.72	10	ZR-
64/1/2/2	2	8.0	11	26	-1.1	-2.2	100.39	10	ZR-F
64/1/2/3	2	6.4	11	24	0.0	-0.6	100.09	10	ZR-F
64/1/2/4	2	4.8	11	32	1.1	0.6	99.63	10	R-F
64/1/2/5	2	3.2	14	48	2.8	2.2	99.20	10	R-F
64/1/2/6	3	1.2	16	40	3.9	3.9	98.92	10	R-F
64/1/2/7	2	2.0	20	35	4.4	4.4	98.78	10	F
64/1/2/8	2	4.8	20	29	3.9	3.3	98.70	10	F
64/1/2/9	4	4.0	20	35	3.3	2.8	98.65	10	R-F
64/1/2/10	6	8.0	20	35	2.8	2.2	98.60	10	F
64/1/2/11	8	8.0	20	32	2.8	2.2	98.45	10	F
64/1/2/12	9	9.7	23	29	2.2	1.7	98.43	10	F

hourly observations preceding and including time t as represented by:

$$\bar{a}(t) = (a(t-12), a(t-11), \ldots, a(t))$$

4.2 Similarity measure

Twelve similarity-indicating attributes are identified in Table 2. All of these attributes are almost continuous except for precipitation.

For each continuous attribute, x_i, the expert specifies values of c_{i1}, c_{i2}, and c_{i3} that are thresholds for considering two such attributes to be *very near*, *near*, and *slightly near* each other, respectively (see Figure 1). The similarity measure that we propose is as follows:

$$\mu(\bar{a}(t), (\bar{a}(t'))) = \wedge_{i=0}^{i=m} \wedge_{j=0}^{j=12} (\mu_i(a_i(t-j), a_i(t'-j)) \vee \mu_f(-j))$$

where $\bar{a}(t) = (a(t-12), a(t-11), \ldots, a(t))$ and μ_f is an expert-defined forgetting function that assigns less weight to less recent weather data.

The k-nearest neighbour algorithm then searches the set of all past cases resulting in a set:

$$Nk(\bar{a}(t)) = \{\bar{a}(t_0), (\bar{a}(t_1), \ldots, \bar{a}(t_{k-1})\}$$

of potential analogues to case $\bar{a}(t)$. The search is efficient because computation of the minima allows short circuit evaluation of the similarity measure: an evaluation process is terminated and a candidate analogue case is ruled out of the k-nn set if any measured similarity values between compared attributes are less than the lowest similarity of the k-nn cases found thus far in case base traversal.

The value of the jth forecast parameter at time $t + n$ is then computed as $a(t + n)$ where

$$a_j(t+n) = \sum_{i=0}^{k-1} \mu(\bar{a}(t), (\bar{a}(t_i)) \times a_i(t_i + n)) \div \sum_{i=0}^{k-1} \mu(\bar{a}(t), (\bar{a}(t_i)))$$

Or, in words, $a_j(t + n)$ equals a sum of analagous cases' past parameters, where each case is weighted according to its overall degeree of similarity in the present case.

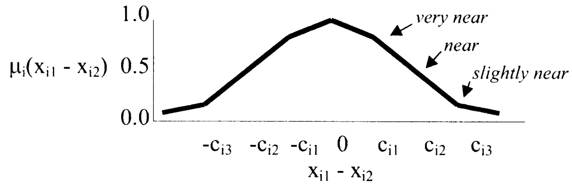


Figure 1 Fuzzy membership function for measuring degree of similarity between two continuous attributes

Table 3 Flying categories (note 2: VFR is short for Visual Flight Rules and IFR is short for Instrument Flight Rules. VFR and IFR are two exclusive categories of flying conditions. When IFR conditions are forecast, pilots need extra training and instruments

ceiling (m)		visibility (km)	flying category
< 200	or	< 3.2	below alternate
≥ 200	and	≥ 3.2	alternate
≥ 330	and	≥ 4.8	VFR [1]

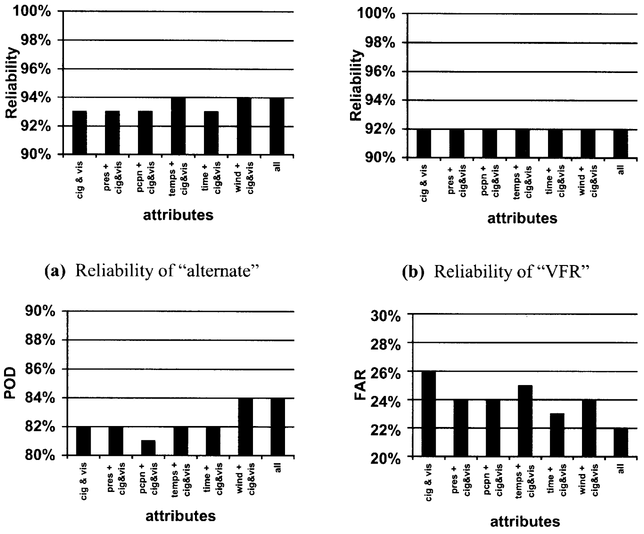
5. EXPERIMENTS

The quality of TAFs is determined by the accuracy of the forecast weather elements and the timeliness of issue. The Meteorological Service of Canada measures TAF quality in four ways: with three ceiling and visibility accuracy statistics and with a speed-of-amendment statistic [6]. The commonest cause for amendments is an incorrect forecast of ceiling or visibility [23]. Timeliness refers to the time between TAF issue and the decision deadline of the intended user, or in other words, the amount of time the TAF can be used to affect critical decisions about flight scheduling. In our experiments we address accuracy of forecasts of three significant flying categories (see Table 3).

Each experiment consists of a forecasting scenario. Five sets of experiments are conducted. In each set of experiments we systematically change the fixed parameters of WIND-1 and measure the resultant effects on forecast accuracy. The fixed parameters (independent variables) are: the attribute set, the number of analogues used to make forecasts, the size of the case base, and the fuzzy membership functions. The output (dependent variables) are, for each individual forecast, forecast values of cloud

Table 2 Twelve attributes of an airport weather observation (METAR)

Category	Attribute	Units
temporal	date hour	Julian date of year (wraps around) hours offset from sunrise/sunset
cloud ceiling and visibility	cloud amount(s) cloud ceiling height visibility	tenths of cloud cover (for each layer) height in metres of ≥ 6/10ths cloud cover horizontal visibility in metres
wind	wind direction wind speed	degrees from true north knots
precipitation	precipitation type precipitation intensity	"nil", "rain", "snow", etc. "nil", "light", "moderate", "heavy"
spread and temperature	dew point temperature dry bulb temperature	degrees Celsius degrees Celsius
pressure	pressure trend	kiloPascal · hour $^{-1}$



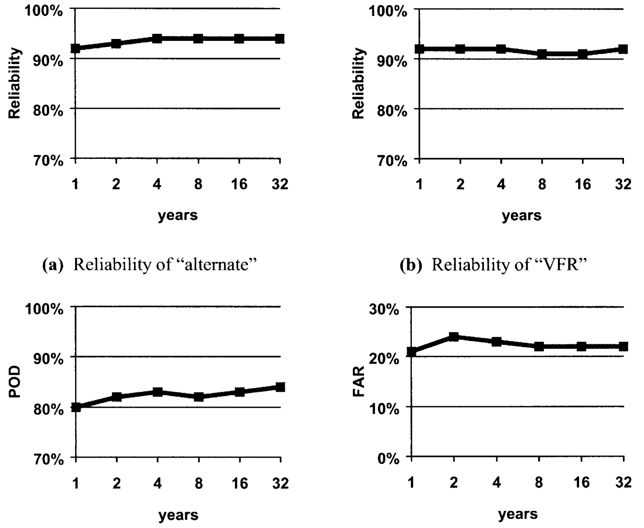
(a) Reliability of "alternate"

(b) Reliability of "VFR"

(c) Probability of Detection of "below alternate"

(d) False Alarm Ratio of "below alternate"

Figure 2 Effect of varying attribute set. Graphed values are average accuracy of 0-to-6-hour predictions. System configuration: k = 16, length of case base = 35 years. (Note: Combinations of weather attributes considered are: 1) cig & vis – cloud ceiling height and visibility alone; 2) pres + cig & vis – mean sea level pressure and cloud ceiling height and visibility; 3) pcpn + cig & vis – precipitation type and cloud ceiling height and visibility; 4) temps + cig & vis – dry bulb temperature and dewpoint temperature and cloud ceiling height and visibility; 5) time + cig & vis – time of day and time of year and cloud ceiling height and visibility; 6) wind + cig & vis – wind speed and direction and cloud ceiling height and visibility; and 7) all of the aforementioned attributes.)



(a) Reliability of "alternate"

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Figure 3 Effect of varying size of case base. Graphed values are average accuracy of 0-to-6-hour predictions. System configuration: k = 16

ceiling and visibility, and, for each set of experiments, a summary of the accuracy of all the forecasts made.

In each set of experiments, 1000 hours are chosen at random from the 1996 weather archive and are each used as a forecast hour. So, in each set of experiments, 1000 simulated forecasts are produced. For purposes of comparison, the same 1000 randomly-chosen hours are used in each set of experiments. This is a control so that the effect of varying other input can be tested.

In each individual experiment, a case is taken from the 1996 data and is used as a present case. It is input to WIND-1. During the forecast process, the outcome of the present case is hidden from WIND-1. WIND-1 produces a forecast for the present case based on the outcomes of the k-nn most analogous past cases for the present case. After the forecast process, the accuracy of the forecast is verified by comparing the forecast with the then unhidden outcome of the present case using standard meteorological quality control statistics [6]. In the following figures, high forecast accuracy is indicated by high reliability, high probability of detection, and low false alarm ratio.

For a given event category, A, reliability equals the number of times when A is forecast to occur and it did occur divided by the sum of the number of times A is forecast to occur and is did occur and the number of times it was forecast to occur and it did not occur, e.g., if the reliability of a forecast of A is 90%, that means that 90% of the time that A is forecast to occur, it occurs, i.e., such a forecast is 90% reliable.

Probability of detection equals the number of true positives divided by the sum of the number of true positives and the number of false negatives, i.e., the probability that an event is correctly forecast given that it does occur.

False alarm ratio equals the number of false positives divided by the sum of the false positives and the true positives, i.e., the probability that an event does not occur given that it is forecast to occur.

5.1 Attribute set

The first set of experiments varies the attribute set and shows that prediction accuracy increases as the number of attributes used for comparison increases (see Figure 2).

5.2 Size of the case base

The purpose of this experiment is to determine the effect of varying the size of the case base in order to assess the importance of having a large case base. As the size of the case base increases, supposedly, more and more potential good analogues are available for the fuzzy k-nn algorithm upon which to base predictions. This experiment addresses the question: "Is the fuzzy k-nn predictions method effective with a small case base, or does it require a large case base?" This question is of practical importance because sizes of weather archives vary greatly from one airport to another. The size of the case base is varied and the results are shown in Figure 3.

Accuracy generally rises as the size of the case base size increases from 1 year to 32 years, although there appears to be a slight dip in accuracy for a case base size of 8 years (b) and (c). The general rise in accuracy suggests that having a large case base is beneficial. The slight dip in accuracy for a case base size of 8 years though only 1%, may suggest that, for the purposes of predicting for weather sit-

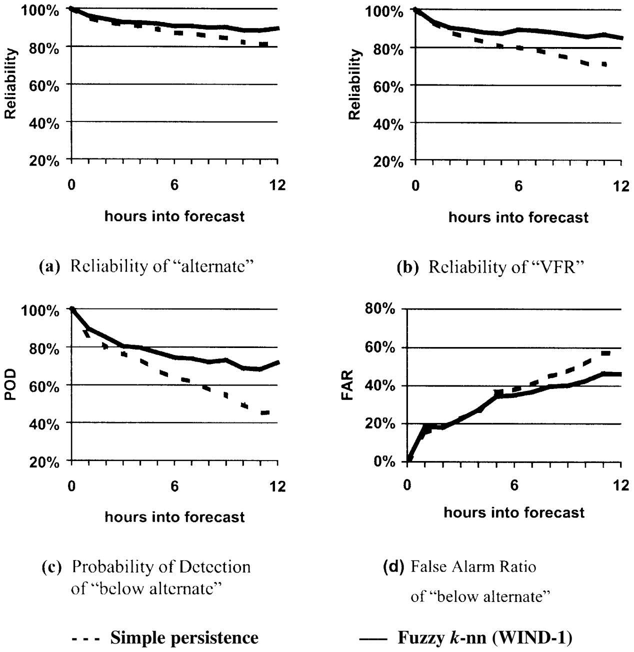


Figure 4 Effect of varying size of case base. Graphed values are average accuracy of 0-to-6-hour predictions. System configuration: k = 16

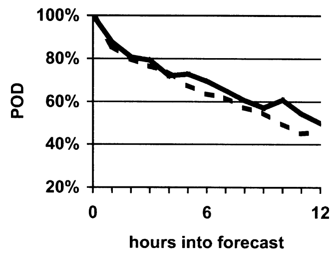
uations in the year 1996, the four-year period 1992–1995 contains a higher proportion of good analogues than the 8-year period 1988–1995.

Significantly, the relatively high accuracy with a case base size of 4 years suggests that the WIND-1 system could be useful for predicting at airports with relatively small weather archives. Most airports have recorded weather for at least 4 years.

5.3 Comparing WIND-1 with persistence climatology

As explained in section 2, persistence climatology is an analogue forecasting technique that is widely recognized as a formidable benchmark for short-range weather prediction. In this set of experiments we compare the performance of WIND-1 with simple persistence forecasting. The results (in Figure 4) show that in each of the categories the performance of WIND-1 is significantly better than that of simple persistence forecasting.

The accuracy of the system is compared to a benchmark



- - - Simple persistence — Fuzzy *k*-nn (WIND-1)

Figure 5 Probability of Detection of the 'below alternate' using non-fuzzy sets

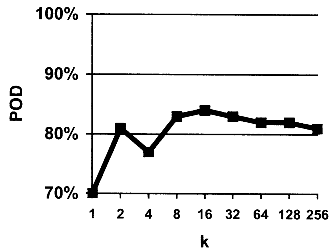


Figure 6 Probability of Detection of 'below alternate'

technique: persistence. Graphed values are standard statistical measures of accuracy of prediction for each hour in the 0-to-12-hour projection period. Persistence forecasting (forecasting no change) is a standard benchmark for measuring short-term forecast accuracy [24].

5.4 Using crisp sets

This set of experiments (of which we show only one) shows the effect of using non-fuzzy sets against persistence. Non-fuzzy sets are made from fuzzy sets by transforming any values below 0.5 to 0.0 and any values at or above 0.5 to 1.0. Comparison of Figure 4c and Figure 5 suggests that, compared to persistence, and compared to using crisp membership for selecting analogues, the use of fuzzy membership functions significantly improves the performance of the WIND-1 system.

5.5 Size of k

In this set of experiments we vary k, the number of nearest neighbors that are used as the basis of predictions (k = 1, 2, 4, 8, ... , 256) and finds that maximum accuracy is achieved with k = 16. This suggests that WIND-1 is effective at identifying and ranking nearest neighbors, or, in meteorological terms, it finds the best analogue ensemble. Assuming that fuzzy k-nn similarity metric is effective, if k is too small, prediction result accuracy should suffer from sample size being too small (i.e., not representative), and if k is too large, prediction result accuracy should taper off because of the inclusion of an increasing number of decreasingly similar cases. Accordingly, Figure 6 shows that the fuzzy k-nn similarity metric is effective.

6. CONCLUSION

Based on our literature review, experiments, and the results presented in our thesis, we conclude that querying a large database of weather observations for past weather cases similar to a present case using a fuzzy similarity measure that is designed and tuned with the help of a weather forecasting expert together with a k-nearest neighbors algorithm and weighted adaptation can increase the accuracy of predictions of cloud ceiling and visibility at an airport.

Of significance to CBR: We have shown how fuzzy logic can impart to CBR the perceptiveness and case-discriminating ability of a domain expert. The fuzzy k-nn technique described in this thesis retrieves similar cases by emulating a domain expert who understands and interprets similar cases. The main contribution of fuzzy logic to CBR is that it enables us to use common words to directly acquire domain knowledge about feature salience. This knowledge enables us to retrieve a few most similar cases from a large temporal database, which in turn helps us to avoid the problems of case adaptation and case authoring. The k-nn algorithm, even though it is of approximate Order(n) complexity, makes superior predictions with practical speed – with less than one minute of computation. This speed is achieved by short circuit evaluation of the infima-expressions, using strategical ordering of the steps in the case-to-case similarity-measuring test and by stopping any test as soon as a step reveals that a case is dissimilar enough to be ruled out of the k-nn set.

Of significance to meteorology and the aviation industry: such a fuzzy k-nn weather prediction system can improve the technique of persistence climatology (PC) by achieving direct, efficient, expert-like comparison of past and present weather cases. PC is an analogue forecasting technique that is widely recognized as a formidable benchmark for short-range weather prediction. Previous PC based systems have had two built-in constraints: they represented cases in terms of the memberships of their attributes in predefined categories and they referred to a preselected combination of attributes (i.e., defined and selected before receiving the precise and numerous details of present cases). The proposed fuzzy k-nn system compares past and present cases directly and precisely in terms of their numerous salient attributes. The k-nn method is not tied to specific categories nor is it constrained to using only a specific limited set of predictors. Such a system for making airport weather predictions will let us tap many, large, unused archives of airport weather observations, ready repositories of temporal cases. This will help to make airport weather predictions more accurate, which will make air travel safer and make airlines more profitable.

We plan to pursue this research and improve WIND-1 by testing its prediction accuracy at other airports; enabling it to learn autonomously; and incorporating additional predictive information, such as user-provided hints, projections of weather radar images of precipitation, projections of satellite images of cloud, and guidance from large-scale computer models of the atmosphere.

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REFERENCES

1. L. J. Battan, *Fundamentals of Meteorology*, Eaglewood Cliffs, New Jersey, Prentice-Hall. pp157–161, 1984.
2. B. J. Conway, Expert systems and weather forecasting, *Meteorological Magazine*, 118, pp23–30, 1989.
3. T. Hall, Precipitation forecasting using a neural network, *Weather and Forecasting*, Boston, 14, Iss. 3; 338–346, Jun 1999.
4. C. Marzban and G. J. Stumpf, A neural network for tornado prediction based on Doppler radar-derived attributes. *J. Appl. Meteor.*, 35, pp617–626, 1996.
5. C. Marzban, A Bayesian neural network for severe-hail size prediction, *Weather and Forecasting*, Boston; Vol. 16, Iss. 5, pp600–611, Oct 2001.
6. B. K. Hansen, Weather Prediction Using Case-Based Reasoning and Fuzzy Set Theory, *Master of Computer Science thesis*, Technical University of Nova Scotia, Halifax, Nova Scotia, Canada, 2001. Online at: http://bjarne.ca/eis
7. H. Stanski, A. Leganchuk, A. Hanssen, D. Wintjes,, O. Abramowski and J. Shaykewich, NAV CANADA's TAF amendment response time verification, *Eighth Conference on Aviation, Range, and Aerospace Meteorology*, 10-15, Dallas, Texas, American Meteorological Society, pp63–67, January 1999.
8. R. E. Huschke (editor), *Glossary of Meteorology, American Meteorological Society*, Boston, Massachusetts, USA, pp 106, 419, 1959.
9. R. L. Vislocky and J. M. Fritsch, An automated, observations-based system for short-term prediction of ceiling and visibility, *Weather Forecasting*, 12, pp31–43, 1997.
10. L. J. Wilson and R. Sarrazin, A classical REEP short-range forecast procedure, *Weather and Forecasting*, 4, pp502–516, 1989.
11. S. S. Allan, S. G. Gaddy and J. E. Evans, Delay Causality and Reduction at the New York City Airports Using Terminal Weather Information Systems, Lincoln Laboratory, Massachusetts Institute of Technology, Lexington, Mass., http://www.ll.mit.edu/AviationWeather/atc-291.pdf, downloaded May 1, 2001.
12. J. Valdez, NWS Reinventing Goals for 2000, National Weather Service, National Oceanic and Atmospheric Administration, United States Department of Commerce, http://www.nws.noaa.gov/npr5.html, downloaded May 1, 2001.
13. R. López de Mántaras and E. Plaza, Case-Based Reasoning: an overview, *AI Communications*, 10, pp. 21–29, 1997.
14. R. Bergman, S. Breen, M. Göker, M. Manago & S. Weiss, *Developing Industrial Case-Based Reasoning Applications The INRECA-Methodology*, Springer: Berlin, 1998.
15. Leake, D. B., CBR in context. The present and future; in Leake, D. B. (ed.), *Case-Based Reasoning: Experiences, Lessons & Future Directions*, American Association for Artificial Intelligence, Menlo Park California, USA, 1996.
16. M. Sebag and M. Schoenauer, A rule-based similarity measure, In *Proceedings of the First European Workshop (EWCBR-93)*, pp119–131, Nov. 1-5, Kaiserslautern, Germany, 1993.
17. J. Surma and K. Vanhoof, Integrating rules and cases for the classification task, In *Proceedings of the First International Conference (ICCBR-95)*, pp325–334, Oct.26-30, Sesimbra, Portugal, 1995.
18. D. Dubois, F. Esteva, P. Garcia, L. Godo, R. López de Mántaras & H. Prade Case-Based Reasoning: A Fuzzy Approach, *Lecture Notes in Computer Science*, Springer, vol. 1566, pp79–91, 1999.
19. T. W. Liao, Z. Zhang and C. R. Mount, Similarity measures for retrieval in case-based reasoning systems, *Applied Artificial Intelligence*, 12, pp267–288,1998.
20, J. M. Keller, M. R. Gray and J. A. Givens, JR, A Fuzzy K-Nearest Neighbour Algorithm, *IEEE Trans. Syst., Man, Cybern.*, vol. SMC-15, 4, pp580–585, 1985.

21. D. B. Leake, CBR in Context: The Present and *The Future, Case-Based Reasoning: Experiences, Lessons, and Future Directions*, D. B. Leake, ed., Menlo Park, Calif., AAAI Press, 1996.
22. W. Wilke, B. Smythe & Pádraig Cunningham, *Using Configuration Techniques for Aaptation, Case-Based Reasoning Technology From Foundations to Applications,* Springer: Berlin, 1998.
23. H. Stanski, 1999. *Personal correspondenc*e.
24. Dallavalle, J. P., and Dagostaro, V. J., The accuracy of ceiling and visibility forecasts produced by the National Weather Service, *Preprints of the 6th Conference on Aviation Weather Systems*, American Meteorological Society, 1995.