FUZZY-LOGIC BASED METHODOLOGIES FOR MOBILE MAPPING: ENHANCING POSITIONING ACCURACY OF GPS/GNSS MEASUREMENTS

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ABSTRACT

This paper shows an application of the fuzzy-logic approach to mobile mapping issues, presenting results of fuzzy processing of the C/A-code-based GPS measurements (standalone static positioning), whose accuracy depends essentially on the satellite observation geometry, expressed numerically by the GDOP (Geometrical Dilution Of Precision) factor, and on the Signal-to-Noise Ratio (SNR). A fuzzy controller, developed in the Matlab environment, is presented together with the envisaged rule base and the design steps (fuzzification, inference engine, defuzzification). A quality index is derived from the fuzzy-logic based data analysis, which allows us to select the "best" GPS observables to be processed in the positioning equations. Experimental results are presented and discussed from real data gathered by a commercial GPS receiver (the Garmin® GPS25-LV 12-channel receiver). Significant improvements of the positioning accuracy have been obtained with respect to the "raw" fixes provided by the receiver, showing the usefulness of the fuzzy-processed position fixes.

1. INTRODUCTION AND BACKGROUND

1.1 Scope and overview

GNSS measurements are affected by perturbations such as ionospheric delays, tropospheric and relativistic effects, interference, multipath, scintillations (Hegarty *et al.*, 2004), time offset effects (Moudrak *et al.*, 2004). The accuracy with which the autocorrelation peak can be determined by the receiver circuitry depends obviously on the pseudorandom transmitted code bandwidth (e.g. 1 MHz for the GPS C/A sequence) as well as on the receiver/correlator architecture (Braasch *et al.*, 2007, Pratt and Owen, 2004), and on the receiver Signal-To Noise Ratio (SNR). In static positioning and land surveying campaigns, a common procedure to increment the measurement accuracy is averaging N measurements, reducing the uncertainty of a factor of $1/\sqrt{N}$, or using interferometric techniques, which demand great occupation time (several minutes) and carrier-phase integer-cycle ambiguity resolution (Cosentino *et al.*, 2006).

This paper exploit an alternative approach to effective accuracy improvement of GNSS measurements, by using additional information related to the quality of the received signal, in order to rank the "optimal" observables and averaging on these selected measurements. The fuzzy-logic based approach has been recently proven to be effective for a wide range of applications, from generic systems engineering to robust estimation and data quality assessment in GPS positioning applications, exploiting carrier- and code-phase measurements (Lin *et al.*, 1996, Mosawi and Muhammadi, 2001, Crocetto and Ponte, 2002, Wieser, 2003). In this work, fuzzy control theory is used to implement this strategy, exploiting the unique ability of fuzzy controllers to translate into numerical algorithms a linguistic formulation of a problem (in our case, the data analysis). As it will be shown in the main body of the work, the methodology identifies indicators of the observation geometry (in particular, PDOP, Position Dilution Of Precision, and TDOP, Time Dilution Of Precision) and the received signal-to-noise ratio (SNR) as input (fuzzy) variables, and provides an output "rating" which qualifies an observable as suitable for accurate measurements. Work has been carried out mainly on GPS C/A code static measurements, but the procedure is easily extendible to more complex measurands, such as carrier phase observables and GNSS/Galileo signals.

After a quick review of some basic concepts (fuzzy logic and fuzzy controllers), results of fuzzy processing of the C/A-code-based GPS measurements (standalone static positioning) are presented. The fuzzy controller, developed in the Matlab environment and the design steps (fuzzification, inference engine, defuzzification) are shown in the paper. A quality index, derived from the fuzzy-logic based data analysis, allows us to select the "best" GPS observables to be processed. Experimental results, gathered by a commercial GPS receiver, show significant improvements of the positioning accuracy.

1.2 Fuzzy logic basics and structure of fuzzy controllers

The mathematical description of linguistic uncertainty based on the idea of fuzzy sets gave birth to fuzzy logic, a rule-based decision-making methodology used for expert systems and process control, aimed at emulating he heuristic, rule-of-thumb approach of human reasoning to many problems. Lack of

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information and knowledge of a phenomenon (informal uncertainty), imprecision of language (linguistic uncertainty) and possibility, rather than probability (not related to "when" it occurs), of occurrence of an event (stochastic uncertainty) are the main issues addressed by fuzzy-logic based control theory. The linguistic control rules devised by human expert to describe and control processes even intuitively and generally, can be directly translated to a rule base of a fuzzy logic controller or an expert system, starting from some *linguistic variables* (LV) which represent some property (for example, the "observation geometry", or the "satellite elevation" for GPS and GNSS measurements). Since Lotfi Zadeh's work in the 1960s (Zadeh, 1960, Zadeh, 1988), which developed fuzzy set theory and generalised the set notion, allowing partial membership of an element to a set and multivalued logic values between TRUE (1) and FALSE (0), the basis of fuzzy logic theory have evolved in a complete and exhaustive mathematical treatment (Zimmerman 2001). The interested reader can consult Kosko, 1992, Klir and Folger, 1988 and McNeil and Freiberger, 1993 for a thorough approach to these topics. We will summarize only the relevant issues pertaining fuzzy logic and fuzzy controllers.

A *linguistic term* (LT) is defined by a *membership function* $\mu(x)$, which can take interval values between 0 and 1, and can be interpreted as the degree of truth to which a measurement x of a quantity satisfies the linguistic concept of a certain term (for example, "low", or "medium") of a linguistic variable (for example, "satellite elevation"). A fuzzy set S (or a LT) is generally expressed as a collection of the elements *x* of a "universe" of measurements U (Berkan and Trubatch, 1997), respectively continuous and discrete:

$$S = \{(x, \mu_S(x))\} = \bigcup_{x_i \in U} \mu_S(x_i)/x_i, \quad x \in U \tag{1}$$

where the x_i are the finite elements of a discrete universe, and the symbol "/" denotes "related to x_i".

A degree of membership $\mu_S(x)$ to an element of the (fuzzy) set labelled with the LT is assigned based on a property. Ffor example, the (crisp) value 3, taken from a universe between 1 and infinity, which represents the "base variable", could belong to the fuzzy set "Acceptable" of the LV "GDOP" with a membership of 0.7. In this context, such fuzzy sets represent LTs. Standard membership functions include Z-type, Λ-type (triangular shape), Π-type (rectangular/trapezoidal), S-type (sigmoidal) and singletons. We will use in this work the Z-type, bell (Gaussian) and sigmoidal functions, as well as triangular functions, for the fuzzy sets "low", "medium" and "high" (Fig. 1).

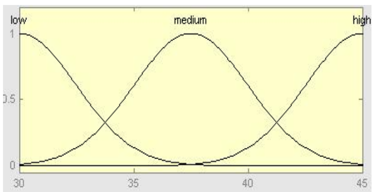


Figure 1. Membership functions of the output fuzzy sets (LTs) "medium", "low" and "high" of the input LVs used in Sec. 2

The parametric expressions are given respectively by:

$$Z(x,a,c) = \begin{cases} 1, & x \le a \\ 1 - 2\left(\dfrac{x-a}{b-a}\right)^2, & a \le x \le \dfrac{a+b}{2} \\ 2\left(\dfrac{b-x}{b-a}\right), & \dfrac{a+b}{2} \le x \le b \\ 0, & x \ge b \end{cases}$$

$$b(x,\sigma,c) = e^{-\frac{(x-c)^2}{2\sigma^2}} \tag{2}$$

$$S(x,a,c) = \frac{1}{1+e^{-a(x-c)}}$$

A typical rule base of a fuzzy controller (Fig. 2) consist of consistent (i.e. non-contradicting) IF-THEN statements (involving LVs and LTs) logically linked by OR-type connectives, that is, defined alternatively. In most applications a linguistic variable is well identified by three to seven or nine LTs (usually an odd number of terms, due to the symmetrical definition of the terms themselves). Considering K input LVs, and J_1, J_2, …, J_K LTs for each of the input LV, L output LVs and M_1, M_2, …, M_L output LTs, there are at most $J_1 \cdot J_2 \cdot \ldots \cdot J_K$ different rules available to form a consistent rule base. These rules are organisable in a square K-dimension hypermatrix, easily visualized when K=2 and L=1 (two-input, one-output fuzzy systems). If we have K input variables with J terms each, the total number of possible rules is J^K.

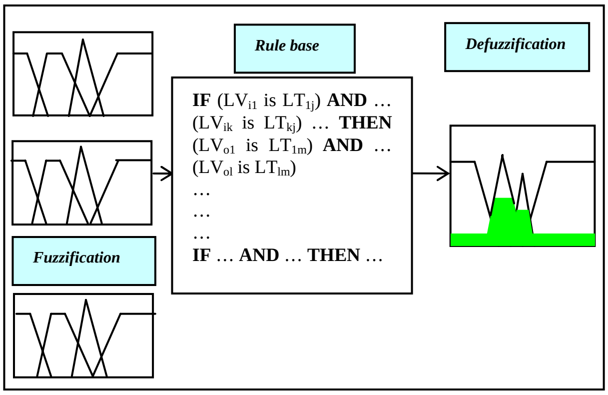


Figure 2. Conceptual structure of a fuzzy controller

Translating real variables (crisp values) into linguistic variables is the process of *fuzzification*, which associates an input value x_i with a membership vector pertaining to the k-th input LV:

$$x_i \begin{cases} LT_{k1} \to \mu_{k1}(x_i) \in [0,1] \\ LT_{k2} \to \mu_{k2}(x_i) \in [0,1] \\ \ldots \\ LT_{kJ} \to \mu_{kJ}(x_i) \in [0,1] \end{cases} \to [\mu_{k1}(x_i), \mu_{k2}(x_i), \ldots, \mu_{kJ}(x_i)]^T \tag{3}$$

where the superscript T denotes transposition. Deriving a conclusion from the rule base that represents the control strategy is the *fuzzy inference* step, whose result is some LT_o of an output LV. Needless to say, the rule base determines the principal functionality of the controller. Translating the resulting LT_o into a real value representing the crisp value of the control variable, is the *defuzzification*.

The fuzzy inference generally consists of two components: aggregation, i.e. evaluation of the degree of truth of the condition, the IF-part of each rule, which is “activated” by the non-zero membership functions associated with the crisp input x_i, and composition, i.e. evaluation or weighting of the conclusion, the THEN-part (Jantzen, 1999). The connectives AND, OR, NOT are not to be intended in the classic, Boolean sense, and are describable in different ways (…). The most commonly used are $\min(\mu_{k1}(x_i), \dots, \mu_{kJ}(x_i))$ for AND, $\min(\mu_{k1}(x_i), \dots, \mu_{kJ}(x_i))$ for OR, and $1- \mu_{kJ}(x_i)$ for NOT. This is usually called a *max-min inference* rule base (Berkhan and Trubatch, 1997). Figure 3 conceptualizes the design flow of a fuzzy controller.

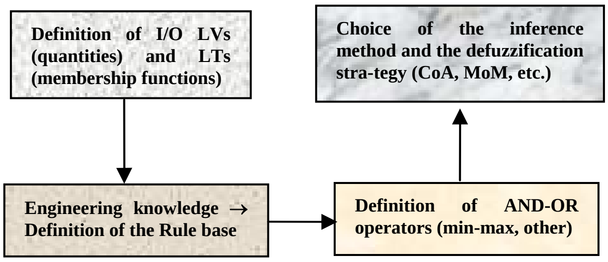


Figure 3. Fuzzy controller design steps

Concerning the defuzzification step (Mendel, 1995), in the centroid, or Center of Area (CoA) methodology the μ-functions representing the conclusion terms are truncated at the degree of validity of the rule to which the THEN terms belongs, then the areas under the resulting truncated membership functions are superimposed and the geometric center of the resulting area is taken as the desired crisp output value. A modified CoA method allows the output value to vary within the entire output universe. In the Center of Maximum (CoM) approach the output crisp value is computed by a weighted sum of the typical values of the LT_o (i.e. the values of the output universe where the μ’s are maximum), the weight being the degree to which the action term (the THEN-part) is true. In the Mean of Maximum (MoM) technique the most plausible result is evaluated, selecting the typical value of the most valid LT_o. This approach is well suited for classification and pattern recognition, and gives a stepped input/output characteristic of the controller.

2. FUZZY LOGIC IN GPS POSITIONING: ALGORITHMS AND RESULTS

2.1 Hardware and data acquisition

GPS C/A code measurements have been gathered by the OEM (Original Equipment Manufacturer) 12-channel receiver GPS25 made by Garmin (Garmin, 2000, Garmin, 2007, Fig. 4). The GPS 25 Series offers a compact profile that includes a realtime clock, PPS (Pulse Per Second) timing output, non-volatile memory, differential GPS capability, and raw measurement output for both pseudorange and phase data at 1 Hz (one fix per second). The board (version 25-LVC) has -165-dBW sensitivity, accepts power from unregulated low voltage supplies between 3.6 and 6 VDC, with 800 mW typical consumption. Asynchronous serial data interfaces via 2 serial ports with CMOS voltage level outputs or RS-232 polarity. All serial inputs are compatible with either true RS-232 or TTL/CMOS voltage levels. Port 1 uses the National Marine Electronics Association (NMEA) 0183 data format (Betke, 2002, NMEA 2007). Port 2 transmits binary position and raw measurement data and receives differential corrections data. The declared positioning accuracy is 15 m.

Figure 4. Garmin GPS25 sensor board

The board was connected in our experiments to a Pentium-4-based PC with 2.6-GHz clock. A set of software routines has been developed by the authors for logging the data of interest.

The main NMEA sentences used in this work are as follows:

1. Global positioning fix data (GGA): provides 3-D location, time and accuracy data. The format is:

$GPGGA , <1>, <2>, <3>, <4>, <5>, <6>, <7>, <8>, <9>, M, <10>, M, <11>, <12> *hh <CR> <LF>

where:
<1> UTC time of the position fix (format: hhmmss)
<2> Latitude, ddmm.mmmm
<3> Latitude Hemisphere, N or S
<4> Longitude, dddmm.mmmm
<5> Longitude Hemisphere, E or W
<6> GPS quality indicator. 0= no fix, 1= non-DGPS fix
<7> Number of used satellites, from 00 to 12
<8> Horizontal dilution of precision (HDOP), from 0.5 to 99.9
<9> Antenna altitude above/below mean sea level, from -9999.9 to 9999.9 m
<10> Geoidal separation (undulation) with respect to WGS-84 ellipsoid, from -999.9 to 9999.9 m
<11> Age of DGPS data, seconds elapsed from last RTCM valid transmission (null if not DGPS)
<12> Differential reference station ID, from 0000 to 1023 (null if not DGPS)

2. GPS DOP and active satellites (GSA). This sentence provides details on the nature of the fix. It includes the numbers of the satellites being used in the current solution and the DOP. The format is:

GPGSA, <1>, <2>, <3>, <3>, <3>, <3>, <3>, <3>, <3>, <3>, <3>, <3>, <3>, <3>,<4>,<5>,<6>,*hh <CR> <LF>

where:
<1> Mode, M= manual, A= automatic
<2> Fix type, 1 =not available, 2=2-D, 3 =3-D
<3> PRN number, from 0 to 32, up to 12 transmitted
<4> Position Dilution Of Precision (PDOP), from 0.5 to 99.9
<5> HDOP, from 0.5 to 99.9
<6> Vertical Dilution Of Precision (VDOP), from 0.5 to 99.9

3. Satellites in view (GSV). It shows data about the satellites that the unit might be able to find based on its viewing mask and almanac data. One GSV sentence only can provide data for up to 4 satellites, therefore there may need to be 3 sentences for the full information. The GSV sentence could contain more satellites than GGA might indicate since GSV may include satellites not used as part of the solution. The SNR field (or

Carrier-To-Noise Ratio, C/N_0), often referred to as “signal strength”, is an indirect but more useful value than raw signal strength. It can range from 0 to 99 dB according to the NMEA standard, but various manufacturers send different ranges with different starting numbers, so the values themselves cannot necessarily be used to evaluate different units. The range will usually show a difference of about 25 to 45 between the lowest and highest values. In our experiments, the SNR excursion has been found to be in the interval [39, 44] (Fig. 5).

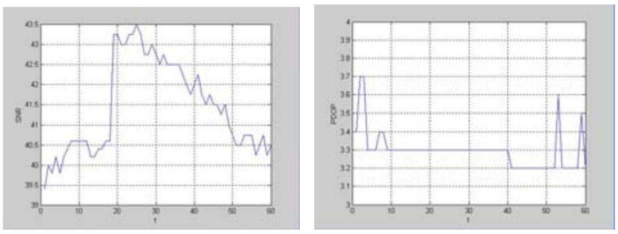


Figure 5. Variations of the observed SNR and PDOP in the collected data

The format of the sentence is:

GPGSV, <1>, <2>, <3>, <4>, <5>, <6>, <7>, …, <4>, <5>, <6>, <7>, *hh <CR> <LF>

where:
<1> Total number of GSV sentences to be transmitted
<2> Number of current GSV sentences
<3> Total number of satellites in view, from 00 to 12
<3> Satellite PRN number, from 0 to 32
<5> Satellite elevation, from 00 to 90 degrees
<6> Satellite azimuth, true, from 000 to 359 degrees
<7> SNR/Signal strength (C/N_0), from 00 to 99 dB (null when not tracking)

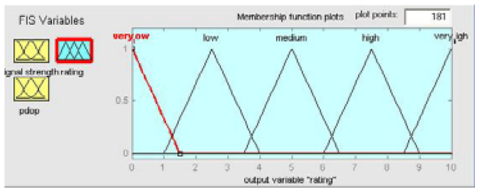
4. Estimated errors (PGRME). This is a proprietary (“P”) sentence, “GRM” is the manufacturer code (Garmin). The format is:

PGRME, <1>, M, <2>, M, <3>, M, *hh <CR> <LF>

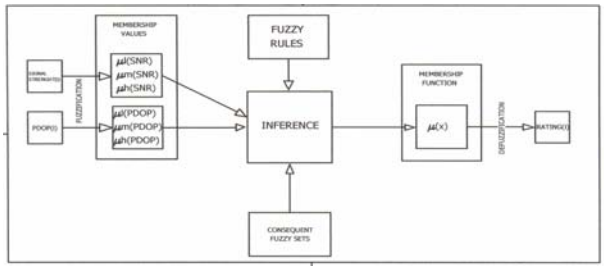
where:
<1> Estimated horizontal position error (HPE), 0.0 to 999.9 m
<2> Estimated vertical error (VPE), 0.0 to 999.9 m
<3> Overall spherical equivalent position error (EPE), 0.0 to 999.9 m.

2.2 Fuzzy controller design

The fuzzy controller was designed using the Matlab® Fuzzy Logic Toolbox (The Mathworks, Inc., 2005). Following the conceptual scheme depicted in Fig. 3, the input (linguistic) variables, gathered by the receiver, used in the design of the fuzzy controller are the PDOP and the average of the SNRs of the four satellites chosen for the position fix, whereas the output fuzzy variable is the “rating”, i.e. an estimate of the quality of the solution, defined in a universe from 0 to 10 and linguistically characterized by five triangular membership functions, labelled “very low”, “low”, “medium”, “high” and “very high” (Fig. 6a). Fig. 6b depicts the fuzzy controller. The corresponding input LTs are associated with three membership functions labelled “low”, “medium” and “high” respectively (Fig. 1).



(a)



(b)

Figure 6. (a) Membership functions of the output LV “rating”; (b) block diagram of the fuzzy controller

The rule base of the two-input, one-output controller consists of nine rules and is illustrated in matrix form in Table 1, where the elements of the matrix represent the implication part (THEN), and the input variables, together with the corresponding LTs, or μ-functions, address each consequent of the rule. The OR connective has been chosen only for the rules 4, 7 and 8, e.g. *IF* SNR is low *OR* PDOP is medium *THEN* Rating is low (rule 4, second row, first column). The LT “very low” is associated to a modified version of the μ-function “low”, $\mu_L(x)$, with the Concentration operator (linguistic hedge, Mendel, 1995):

$$\mu_{con(VL)}(x) = [\mu_L(x)]^2 \quad (4)$$

		SNR		
		Low	Medium	High
PDOP	Low	*Medium*	*High*	*Very high*
	Medium	*Low*	*Medium*	*High*
	High	*Very low*	*Low*	*Medium*

Table 1. Rule base of the fuzzy controller

Similar reasoning is applied to $\mu_{VH}(x)$, for the LT “very high”. Figure 7 visualizes the rule base with the corresponding membership functions. In the example, the input crisp values are 40 and 3 for signal strength and PDOP respectively, and 3.8 is the (defuzzified) crisp output rating. The rules activated by the input values correspond to the shaded membership functions.

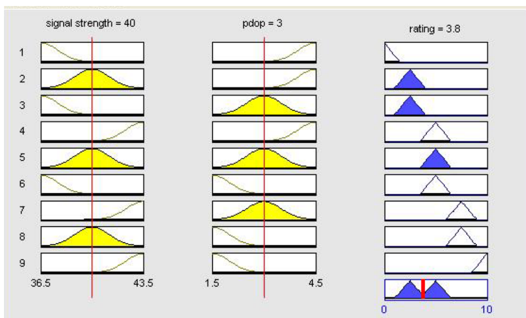


Figure 7. Rule viewer

Different rule bases have been implemented, in order to optimize the sensitivity of the output (rating) with respect to the variations of the input values: for example, a rule base consisting of only AND-connected antecedents (see Tab. 1) gives an “output surface” which yields maximum rating for minimum PDOP and maximum signal strength (Fig. 8).

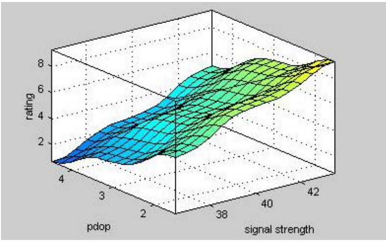


Figure 8. Surface viewer for AND-connected antecedents in the rule base of Table 1

Different choices of the membership functions (for example, triangular also for the input LVs, or singletons for the output rating) have been experimented as well, in order to tune the controller for acceptable results. Figure 9 shows the output rating derived from six different controllers, obtained from combinations of the rule base and the membership functions, showing the measurement quality in four extreme situations (SNR=36.5 and 43.5, PDOP=1.5 and 4.5).

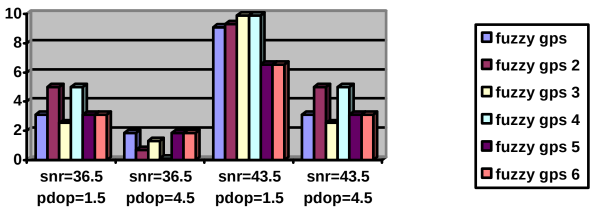


Figure 9. Ouput rating in four extreme cases, for the six controllers designed

The criterion used in the defuzzification phase is the CoA (centroid), obtained from the aggregation of the fuzzy sets pertaining to the rules activated by the crisp input values:

$$\mathrm{CoA} = \frac{\int_U x\mu_k(x)dx}{\int_U \mu_k(x)dx} \tag{5}$$

where $\mu_k(x)$ is the membership function of the k-th LV, and U is the universe, or support, of the variable.

2.3 Results

GPS C/A code measured pseudoranges have been gathered in different observation campaigns, with acquisition times from 60 s (i.e., 60 static fixes) to 15 minutes (900 fixes). The fuzzy-processed fixes were the ones with a rating exceeding a selected threshold. Experimental runs on different datasets, used as numerical training data to tune the parameters of the fuzzy controllers and their output surfaces (Fig. 8), led us to set a value of 4.8 for the acceptance threshold. GPS fixes with rating less than the threshold value were discarded, and the “critical” raw measurements were found to be of the order of 40% of the total datasets. The geodetic solutions were converted to ECEF (Earth-Centred, Earth-Fixed) coordinates.

As a numerical indicator of the quality of the position fix, we have chosen the RSS (root-sum-squared) value of the variances of the ECEF x, y, z solutions obtained from all the fixes provided by the receiver and only from the fixes with high rating, filtered by the cascaded fuzzy controller, respectively. In each of the six designed controllers we have noticed better variances: the fuzzy position fix has been found to be up to 4 times more precise than the “raw” solution provided by the board (In Figure 10, RSSF refers to the root-sum-squared values of the fuzzy-derived position fixes, and the RSS value obtained from raw GPS fixes has found to be 3.7 m). Results are shown for 60-s data collections.

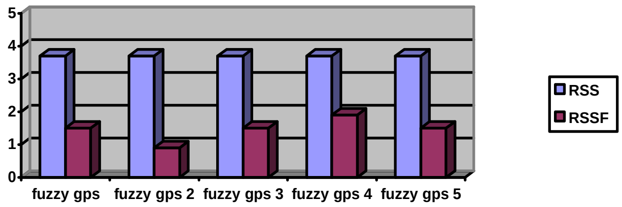


Figure 10. RSS values of the variance of the position fixes obtained by the receiver and by retaining only the solutions with high rating

The RSSF values of the positioning variances obtained with the fuzzy-processed GPS fixes were 1.5, 0.9, 1.5, 1.9 and 1.4 meters, respectively for five of the six controller implemented (the controller labelled “fuzzy gps 6” gave the same results as “fuzzy gps 5”, independent on the choice of the output μ-functions). The increment of precision of the fuzzy-derived fixes has been found to be mainly dependent on the average SNRs of the selected satellite signals, whereas poor PDOPs affected weakly the quality index (rating) and the positioning variances. This is mainly due to the hardware receiver architecture (particularly the correlator section), which is able to identify strong and well-located correlation peaks with high-SNR received signals.

The extensions of the algorithms to Differential GPS (DGPS), carrier-phase measurements and GNSS-2 observables are straightforward, thus proving the feasibility of the fuzzy positioning in the framework of mobile mapping techniques.

3. CONCLUSIONS AND FURTHER WORK

The main result obtained in this work is that fuzzy processing, with its increased flexibility and an implicitly nonlinear approach, improves the positioning accuracy of GNSS-based measurements, by selecting high-rating static fixes using some indicators of the signal quality (PDOP and average SNRs). Experimental results on real GPS static C/A code measurements, delivered by the Garmin® GOS-25LVC sensor board, have shown a reduction by a factor up to 4 of the variances of the ECEF components of the position fixes, filtered by different architectures of the fuzzy controllers, developed in the Matlab® environment, presented in this work. The quality index (“rating”) has been obtained by centroid defuzzification of the fuzzy input sets associated to PDOP and SNRs as measured by a commercial GPS receiver capable of outputting data according to the NMEA protocol.

Our research exploited some advantages of the fuzzy logic approach:

- Ease of modelling (translating linguistic variables and terms into mathematical objects and numbers) and reconfigurability (tuning) of the controller;
- Nonlinear input-output mapping (ease of handling complex dependencies between parameters);
- Real-time implementation (firmware), for use in enhanced receivers;
- Ability of handling different types of uncertainty simultaneously (traditional stochastic approaches need to be tuned to a precise *a-priori* variance models).

As the need for assisted GNSS (A-GNSS) augmentations is becoming critical, due to the rapid modernization of GPS and GLONASS and to the deployment of Galileo, the use of fuzzy logic for improved positioning performance qualifies well as an innovative technology for A-GNSS terminals, where positioning and navigation could be possibly be carried out under prohibitive signal conditions (attenuation, multipath, obstructions, etc.) and a measure of the quality of the observables can provide significant performance improvement of the system, and avoid poor-accuracy standalone positioning.

In addition, the fuzzy approach could be implemented even in dynamic environments, by using real-time algorithms hosted by microcontrollers and fast COTS (Commercial Off-The-Shelf) GPS boards (up to 100-Hz update rate). Alternative criteria for choosing the optimal satellite set (with respect to the traditional minimum-GDOP or all-in-view least-squares approaches) could be envisaged by using fuzzy controllers capable of handling additional information (for example, age of DGPS data).

Finally, the easy implementation of fuzzy reasoning to different types of GNSS observables (carrier-phase in the real-time kinematic (RTK) domain, Doppler shifts for velocity measurements, etc.), or the use of fuzzy controllers for estimation and/or mitigation of other GNSS error sources (satellite orbits, ionosphere group delays, etc) are challenging future fields of application, particularly in the perspective of mobile mapping. Work is currently underway towards developing real-time firmware (micro-controller hosted) implementations of the fuzzy controllers with extended capability (processing of carrier and phase data, use of fuzzy systems in dynamic positioning, handling of differential data) and increased precision and reliability of the results.

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