Hybrid-intelligent Mobile Indoor Location using Wi-Fi Signals
Location Method using Data Mining Algorithms and Type-2 Fuzzy Logic Systems

Manuel Castañón-Puga, Abby Salazar-Corrales, Carelia Gaxiola-Pacheco, Guillermo Licea, Miguel Flores-Parra and Eduardo Ahumada-Tello

Autonomous University of Baja California, Tijuana, Mexico

Keywords: Location, Wi-Fi, Situational Awareness, Fuzzy Logic, Data Mining, Smartphone.

Abstract: Technology with situational awareness needs a lot of information of the environment to execute the correct task at the correct moment. Location of the user is typical information to achieve the goal. This work proposes a mobile application that enables the indoor location of smartphones using the potential infrastructure given by Wireless Local Area Networks. This infrastructure goes beyond GPS (Global Position System) where signal is weak or is not available for indoors. This application uses an alternative and unconventional method to indoor location using Wi- Fi RSSI fingerprinting as well as an estimation based on Type-2 fuzzy inference systems provided by the developed framework JT2FIS. Wi-Fi Fingerprinting creates a radio map of a given area based on the RSSI data from several access points (APs) and generates a set of RSSI data for a given zone location. Consequently Data Mining is required for clustering the obtained set of data and generating the structure of a Type-2 Mamdani or Takagi-Sugeno Fuzzy Inference System; thus new RSSI values are introduced to the Type-2 Fuzzy Inference System to obtain an estimation of the user zone location.

1 INTRODUCTION

The growing technology and advanced algorithms can generate a lot of useful information to be used to improve other tasks. Also with recent advances in technology exists the possibility of connecting different devices using wireless networks to transparently interact with the environment and seamlessly with people. The challenge of this idea is to find ways to know the particular context or situation in time and space to make a decision based on it without the awareness of the user. Devices require algorithms with the ability to understand the context information so that a given system can adapt to it and behave in a certain way. The behavior of a person frequently depends on the context. Human nature enables us to be aware of a lot of variables at a time that influence a person to behavior in a certain way. Context awareness could be a more suitable technological for the needs of the moment. In order to understand the context, it is necessary to have in mind different factors which vary depending on the activity to be performed such as current weather or temperature, atmospheric pressure, lighting from one place, position of an object, the place where a person is, among others. Some other variables are more complex to detect such as the mood of a person or the identity of other persons near the target person. On other hand, there are variables that are useful to determine more of these variables, an example is the location of persons or objects; this can help to detect the number of persons in a room or if certain users are near. The proposed mobile application estimates the indoor location of the user using a hybrid-intelligent method that makes use of Wi-Fi Received Strength Signal Indicators (RSSIs). The data mining and fuzzy logic methods were implemented using the developed JT2FIS framework.

1.1 Situational Awareness

In the past, objects that could understand their environment, communicate and properly respond without the need of direct intervention of man looked distant due to the complexity involved. However, nowadays this is more possible mainly by two factors: because in the last years the technological advancement has been increasing, and also because of the great increase of devices connected to different networks, such as Internet (Sanchez et al., 2014). The context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between

Castañón-Puga M., Salazar-Corrales A., Gaxiola-Pacheco C., Licea G., Flores-Parra M. and Ahumada-Tello E..
Hybrid-Intelligent Mobile Indoor Location Using Wi-Fi Signals - Location Method Using Data Mining Algorithms and Type-2 Fuzzy Logic Systems.
DOI: 10.5220/0005369806090615
In *Proceedings of the 17th International Conference on Enterprise Information Systems* (ICEIS-2015), pages 609-615
ISBN: 978-989-758-096-3

a user and an application, including the user and applications themselves (Dey, 2001). Devices with the capability of understanding the context are an important key for the non-human intervention in technology tasks. The context or situational awareness parameter of this work is based on the location of the entity.

1.2 Technologies

Actual location techniques commonly use GPS, Bluetooth, or Radio Frequency Identification (RFID) technologies, among others (Chai et al., 2011). Despite that, a disadvantage of GPS is that the satellite signals are blocked by obstacles such as walls, in addition, variations in weather or the presence of buildings results in approximations with errors of meters, so it is not possible to use this system as a method for indoor location (Navarro et al., 2011)(Hwang and Donghui, 2012). On the other hand, Bluetooth technology has limited coverage; this communication is focused on very short distances to achieve the location. Finally RF is an expensive solution since it involves the installation of different sensors in the area where you will estimate the location, so it is not an economically viable method (Navarro et al., 2011). Consequently acceptable alternative techniques are required to fit with established infrastructures and satisfy the functionality of indoor location with ease of use and an affordable cost, as the use of technologies based on Wi-Fi (Chai et al., 2011).

1.3 Location Methods

Triangulation and Trilateration: These methods map RSSI as a function of distance that requires a steep linear characterization curve in order to be properly implemented. Functions describing these curves are then used with live RSSI values as input to generate an (x,y) location prediction (Chai et al., 2011). The disadvantages of these methods are: to carry out the synchronization of these values and that it needs a model to determine the distance according to RSSI values. This work is an alternative solution for localization using a radio map of a given area based on Wi-Fi RSSI data from three (or more) Access Points. Some advantages are that this method works on indoor environments with acceptable coverage, a minimum or null modification of the area infrastructure is required, and is a less expensive option than others (Navarro et al., 2011). The method proposed is based on a FIS (Fuzzy Inference System) using a clustering method (Chiu, 1994), that is a fast, one-pass algorithm for estimating the number of clusters and the cluster centers in a set of data.

2 DATA MINING

The number of generated data is increasing alongside the increase of technology, networks, and sensors. In recent years, the use of new information technologies has come to help handling large amount of data. One evolution of these technologies is the data mining extraction that allows representing knowledge of data store implicitly in big databases. Data mining contributes to understand data and identify patterns, relationships, and dependencies that affect the final results. It creates predictive models that allow undiscovered relationships through the data mining process which are expressed as possible business rules (Crows, 1999). Data mining is a multidisciplinary field that combines techniques from machine learning, pattern recognition, statistics, database, and visualization, to direct it to the extraction and interpretation of a huge database. The data mining focuses on filling the need to discover, predict, and forecast the possible actions with some confidence factor for each prediction (Han and Kamber, 1998). Moreover, it helps to make tactical and strategic decisions, provided the decision power users, is able to measure actions and results in the best way, generates descriptive models to explore and understand the data, and identify patterns, relationships, and dependencies that affect the final results. Creates predictive models that allow undiscovered relationships through the data mining process which are expressed as business rules possible (Crows, 1999). Clustering of numerical data forms is a type of data mining. The aim of clustering methods is to identify natural grouping of data from a large data set, such that a concise representation of the systems behaviour is produced (Ren et al., 2006). Once the clusters of a data set are identified the system behaviour can be translated to the rules of a FIS. Each cluster is translated as one rule of the FIS. Generally more rules describe in more detail the system behavior so a better approximation on the evaluation can be achieved or a better accuracy is gained (Ying et al., 1998). It is important to consider the computational cost and the robustness of the system to define the minimal resources needed to have an acceptable system evaluation. Some cluster features, as size and number, are controlled by the specific parameters involved in different clustering techniques.

2.1 Fuzzy C-Means

Fuzzy C-Means clustering algorithm (FCM) (Bozkir and Sezer, 2013)(Bezdek et al., 1984) makes use of a membership function and centroid computation procedure iteratively to find the best centroid. The FCM is one of the popular clustering algorithms. The effectiveness of the clustering method relies on the distance measure. FCM is the result of combining the c-means approach with the handling of fuzzy data. The result of this combination is adequate because it considers the uncertainty presented in the data, avoiding incorrect results, and creating crisp partitions in a correct way (Bozkir and Sezer, 2013). Additionally the FCM is used to acquire the adequate levels of the set clustering parameters (Yin et al., 2013). In this work the clustering algorithm FCM is used to obtain the fuzzy rules of a Mamdani inference system that is used to estimate the location of a device (smartphone with Wi-Fi) as described in section 3.

2.2 Subtractive Method

Subtractive clustering operates by finding the optimal data point to define a cluster center based on the density of surrounding data points. It reduces the computational complexities and gives better distribution of cluster centers in comparison with other clustering algorithms (Ren et al., 2006). This method considers each point as a potential center and, based on mathematical approximations, calculates the best choice of center. Each cluster center can be considered as a fuzzy rule of the system, and the cluster identified represents the antecedent of this rule. The measure of potential for a data is estimated based on the distance of this data point from all other data points (Vaidehi et al., 2008). The identification of a Takagi-Sugeno (TSK) FLS using clustering involves formation of clusters in the data space and translation of these clusters into TSK rules such that the model obtained is close to the system to be identified.

3 TYPE-2 FUZZY LOGIC

The concept of a Type-2 fuzzy set was introduced by Zadeh (Zadeh, 1965) as an extension of the concept of usually Type-1 fuzzy sets. A Type-2 fuzzy set is characterized by a membership function whose membership value for each element of the universe is a membership function within the range [0, 1], unlike the Type-1 fuzzy sets where the value of membership is a numeric value in the range [0, 1]. The creation of a fuzzy set depends on two aspects: the identification of a universe of appropriate values and specifying a membership function properly. The choice of membership function is a subjective process, meaning that different people can reach different conclusions on the same concept. This subjectivity derives from individual differences in the perception and expression of abstract concepts and it has little to do with randomness. Therefore, subjectivity and randomness of a fuzzy set are the main difference between the study of fuzzy sets and probability theory (Jang et al., 1997). A Type-2 Fuzzy Logic System (FLS) can be used when it is not possible to determine exact membership grades or its uncertainty in the rules (Cai et al., 2007). In Type-1 fuzzy sets, once the membership function is defined for a concept, this is based on the subjective opinion of one or more individuals and shows no more than one value for each element of the universe. In doing so, it loses some of the ambiguity of the discussed concepts, especially where people may have a slightly different opinion, but they are considered valid. The Type-2 fuzzy sets allow handling linguistic and numerical uncertainties. Figure 1 depicts two graphics of fuzzy sets: a) with Type-1 fuzzy logic, and b) with Type-2 fuzzy logic.

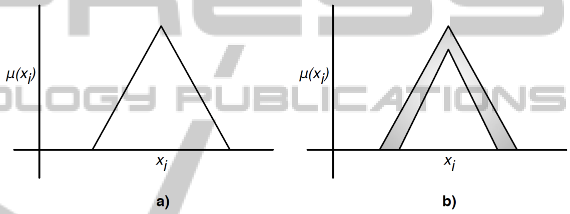

Figure 1: Difference between type-1 and type-2 fuzzy logic membership functions.

The FLS process is divided in four parts: fuzzifier, rule base, fuzzy inference engine, and output processor. In type-2 a type reducer is needed in the output processor to derive a type-1 set from the type-2 set (Cai et al., 2007). Figure 2 shows a diagram with a more detailed example of a FIS structure.

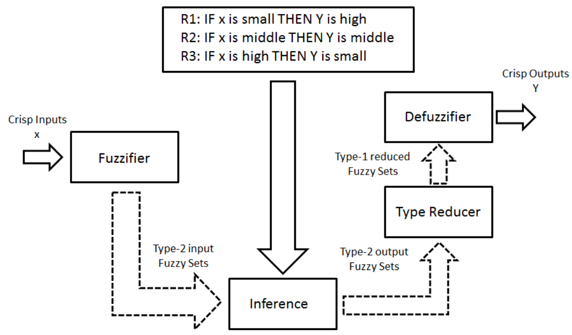

Figure 2: Fuzzy Inference System diagram.

3.1 Mamdani and Takagi-Sugeno FLSs

Mamdani and Takagi-Sugeno FLSs are popular and are formed by IF-THEN rules with the same antecedent structures. The difference between them is in the consequent structures. The consequent of a

Mamdani rule is a fuzzy set while in TSK is a function, so TSK uses fewer fuzzy rules to represent a real system than Mamdani (Cai et al., 2007). TSK FLS was proposed in an effort to develop a systematic approach to generating fuzzy rules from a given input-output data set. This model consists of rules with fuzzy antecedents and mathematical function in the consequent part. The antecedents divide the input space into a set of fuzzy regions, while consequences describe behaviour of system in those regions (Ren et al., 2006).

4 JT2FIS FRAMEWORK

JT2FIS is a class library developed for Java. The main purpose is to deploy a library for building interval Type-2 fuzzy inference systems with an object-oriented programming language. A fuzzy inference system (FIS) is based on logical rules that can work with numeric values or fuzzy inputs; these rules and individual results are evaluated together to form a fuzzy output, then, a numerical value must be passed through a process of defuzzification if necessary. Because it is developed in native Java it is possible to integrate its methods with Android capabilities and the smartphone resources.

4.1 JT2FIS Clustering

JT2FISClustering is a class library developed for Java. The main purpose is to deploy a library to build interval Type-2 fuzzy inference systems with an object-oriented programming language from data mining process. A clustering method is a data mining classic technique used to discover fuzzy sets and rules to congure the FIS from real data. The library implements a Fuzzy C-Means or Subtractive Clustering algorithm for data mining.

5 CASE OF STUDY

There is an interest on detecting the location of people in indoor spaces, such as shopping malls and museums, in order to generate statistics about the interests of the visitors in order to guide the new ideas and improvements of the place to cover those estimated interests. Another advantage of knowing the location of a person is to show them relevant or interesting information related to that place and the profile of the user. Therefore, this case of study proposes the location of children inside an interactive museum with an android mobile device using wireless signals from 3 different Access Points (APs) in the area. The case of study was developed in an interactive museum oriented for kids. This museum has three active floors with different rooms on each one. The collected data was taken in one room on the first floor with approximately twenty interactive modules about science. For experimental purposes the test was divided in two phases, the first with three not so close areas (darker grey). The second collection of data was in four zones (lighter grey) with few meters of distance (1 meter as the minimum distance) as the representation shown in Figure 3. Moreover, 3 APs are strategically positioned for getting enough coverage of the zones to do the triangulation and estimation of the location of the kids.

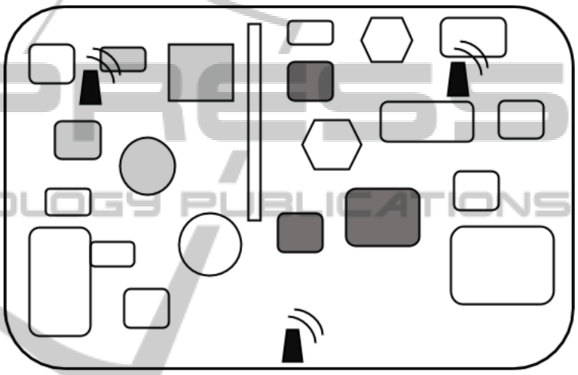

Figure 3: Case of study: zones and Access Points stablished in the museum room.

The objective is to have enough RSSIs values from the selected APs that describe each desired zone; then a clustering method is applied in order to generate the Mamdani or TKS Type-2 FISs to determine the location. An important detail is that the location outside and between the selected zones is possible because when the membership of two outputs is approximately equal and greater than the other output zones, means the child or device is between the two of them. For example, the case of the output of approximately 50% in zone 1, the output of zone 2 of about 50%, and a low membership of zone 3, results in a position in the showroom, meanwhile a 50% in zone 2 and zone 3, could be a zone between them that is the corridor or the hall. And so, a collection and training of data in every area from the place of study is not needed.

5.1 Collecting Location Data

The proposed mobile application uses the JT2FIS class library to implement a fuzzy inference system (FIS) and Fuzzy C-Means or Subtractive clustering methods to do the estimation of the location process. Wireless signals change because of different factors, then the environment conditions when the values for generating a specific FIS were taken, should be as similar as possible to the time when the location was done, or should do a new FIS for best results. The application detects the wireless signals from at least the three selected APs in the area to have enough samples of each different zone from each AP. There are required at least three different APs to be able to do a correct triangulation on the space. No stablished connection in any moment is required with the APs, it is only needed a scan of the RSSIs of the selected APs. The collected data was taken in different zones using a function to do a Wi-Fi scan with an Android device searching RSSIs of three selected APs. The collection of every set of data from each zone was based on a defined limited time. Some factors, such as the total area of the zone, determine how many data you will need to have a good coverage of valid points for that zone. More quantity and diversity of data can help to have less uncertainty to generate and have a better evaluation of the FIS. Table 1 shows samples of data. In this example, three different inputs obtained for the collected data correspond to each of the three AP signals. At the same time, three different outputs were generated (in-line during collection) with a value of one in the corresponding zone the input data was collected. These were saved as .cvs files.

Table 1: Sample of collected data for each zone and the generated outputs.

Zone	Input1	Input2	Input3	Output1	Output2	Output3
1	-78	-74	-54	1	0	0
1	-80	-72	-45	1	0	0
1	-72	-66	-58	1	0	0
2	-76	-60	-58	0	1	0
2	-74	-59	-59	0	1	0
2	-65	-56	-56	0	1	0
3	-65	-66	-64	0	0	1
3	-66	-67	-60	0	0	1
3	-68	-65	-67	0	0	1
...	...	...	...	...	...	...

5.2 Mining the Collected Data

Once the inputs and outputs in location are obtained, the next step is to use the JT2FIS class library specific methods inside the Android application to do the data mining in-line. The first thing to do is the clustering, which consists in detecting the different sets or groups of data in all the collected data. As explained before, each cluster found is a fuzzy rule that describes the location system. Generally more fuzzy rules give us a more descriptive behavior; also an increase on the number of inputs and outputs increases the number of rules and the complexity of the system too. Specifically in location where zones are closer, a more detailed description of the data is needed, thus increasing the number of clusters may help. This can be controlled by the FCM parameter number of clusters or with the influence radio of each center of clusters in Subtractive clustering method.

5.3 Results of Three Not so Close Zones

The first tests were executed in zones with more distance between them (2 meters approximately) as the darker zones seen in Figure 3. Table 2 shows a comparison of results using Fuzzy C-Means clustering method and Mamdani FLS. Increasing the number of clusters will increase the regression coefficient that indicates the similarity grade of the evaluation data with the target real data. Also increasing the number of clusters increases the time of generation and evaluation of the FLS. Taking an acceptable regression coefficient of 0.85, the less rules cost was with a cluster number of 4 with an acceptable coefficient of 0.8677. This evaluation was generated by 1680 data per input in total of the different 3 zones.

Table 2: Comparison table Mamdani 3 inputs 3 outputs.

Clusters	Gen. time (secs)	Eval. time (secs)	Regression coeff.
3	5.09	0.03-0.1	0.7041
4	3.94	0.07-0.121	0.8677
7	20.41	0.07-0.12	0.8881
10	37.27	0.094-0.18	0.8913
15	56.86	0.14-0.21	0.8918
30	97.45	0.26-0.34	0.9005
70	161.66	0.61-0.97	0.9061

On the other hand, Table 3 shows Takagi-Sugeno data with the same values used with FCM with Mamdani. In this case the modified parameter was the influence radius or granularity grade from 0.9 to 0.1. A low radius tends to generate more clusters; the number of clusters is the number of rules obtained. A low radius implies clusters with closer data. High radio implies clusters with dispersed data or low density, so generally will obtain a fewer number of clusters. Also, the approximation to the clusters process is slower in subtractive method than FCM, but even with the same number of found clusters a better regression coefficient is obtained with subtractive and TSK than FCM and Mamdani. Meanwhile, the elapsing time of evaluation decreases on TSK because the operations of the consequent parts are mathematical equations rather than Mamdanis fuzzy sets operations.

5.4 Results of Four Closer Zones

Another test was developed in four zones with less

Table 3: Comparison table Takagi-Sugeno 3 inputs 3 outputs.

Radius	Clusters	Gen. time (secs)	Eval. time (milli secs)	Regression coeff.
0.9	4	217.96	3.1 - 3.8	0.7361
0.7	4	217.91	3.1 - 5.2	0.9143
0.5	4	220.90	3.3 - 5.5	0.9245
0.4	4	224.36	4.2 - 5.1	0.9307
0.3	4	235.08	3.1 - 4.0	0.9345
0.2	8	222.05	7.0 - 10.0	0.9528
0.1	19	242.30	12.4 - 17.8	0.9741

distance between them, as shown in the lighter grey zones in Figure 3. This set of data is about 1344 data for each input and for each zone or output. Is difficult to identify the grade of membership of the points because of the low distance between each zone (about 1 meter approximately). As shown in Table 4, even with 150 clusters in FCM, the regression coefficient is very low and the evaluation time cost is more than 2 seconds in that case.

Table 4: Comparison table Mamdani 3 inputs 4 outputs.

Clusters	Gen. time (secs)	Eval. time (secs)	Regression coeff.
4	10.6563	0.0035 - 0.0041	0.3296
5	15.7962	0.069 - 0.145	0.3680
10	30.7855	0.15 - 0.23	0.3969
30	70.7959	0.39 - 0.56	0.4573
...	...	...	...
100	155.2	1.42 - 1.5	0.4264
150	165.8371	2.0 - 2.32	0.4776

Table 5 shows information of the generation and evaluation of the set of data using subtractive clustering method and TSK FLS. To achieve the desired regression coefficient, a lower influence radius was needed (0.1), however was not able to be successfully executed in the test device. The regression coefficient with a 0.1 radius was obtained with Matlab tools, and the number of rules obtained was 153. Again the evaluation time is slower in Mamdani rather than TSK FLS, but subtractive is slower than FCM.

Table 5: Comparison table Takagi-Sugeno 3 inputs 4 outputs.

Radius	Clusters	Gen. time (secs)	Eval. time (milli secs)	Regression coeff.
0.9	4	154.4764	0.0560 - 0.17	0.5237
0.7	4	155.6307	0.0390 - 0.022	0.5219
0.5	4	158.0025	0.0088 - 0.0037	0.5173
0.4	6	154.6215	0.0052 - 0.007	0.5343
0.3	12	161.7910	0.01100 - 0.016	0.5874
0.2	31	198.2	0.021 - 0.048	0.7475
0.1	-	-	-	0.9875

5.5 Information of Devices

The device to sense the RSSIs from each AP and where the tests were executed is a Samsung Galaxy Tab 4 7.0, 1.4Hz Quad Core Processor, 4KmAh Battery. The three routers or APs used were a Belkin Wireless G Router 2.4 GHz-802.11g model no. F5D7230-40, an AirPort Extreme by Apple model no. A1034 and a D-Link Wireless Router 2.4 GHz-802.11g model DI-524.

6 CONCLUSIONS

This paper introduced a location on indoor areas method using Wi-Fi signal networks, Type-2 fuzzy inference system approach with a clustering method, and how this can help to make applications that help users in real time depending on the context. On this approach, data was collected by one mobile device that sensed Wi-Fi signals from real indoor areas. Then, we built a Java Type-2 fuzzy inference system using C-Means and Subtractive clustering algorithm. The obtained fuzzy system can be Mamdani or TSK type which is later used to evaluate future signals on mobile devices in order to decide the current localization area. FCM is quicker than subtractive but it is recommended only when having an idea of the patterns in the collected data, otherwise is complicated to estimate an acceptable number of clusters to have an acceptable FLS structure. Other types of pre-processing techniques can be implemented to solve this problem. Subtractive is slower to identify the centers but gives better results once possible optimal centers are found. An expert is not necessary to estimate the number of clusters; in less iterations it is possible to find optimal centers. For evaluation, TSK is better than Mamdani because it is desired to estimate the location of the device in real time, and evaluation in Mamdani implies more processing becoming slower. As future work, we are planning to use a neuro-fuzzy system in order to improve precision on how to produce the fuzzy inference system from data. Also a found limitation of this proposed method is the distance between the zones to locate. It is not implementable in mobile devices when the distance between zones is approximately about less than 1.5 meters. There are details to test using Wi-Fi devices about variety of the signals depending on the number of persons in the places, or position of objects, and temperature, also the impact of adding one more input (AP) to the system. This information is unknown in this work; actually there are considerations to improve about lost signals of APs during location, so a strategy to solve this problem is still in construction. Finally for an evaluation of the method, a regression between target and outputs values gives a better idea of the behavior of the FLSs depending on the parameter of the clustering methods, but a final and correct evaluation of the system with a confusion matrix will achieve this goal. Also to generate the FISs and evaluate them in this work the same values were used, so it is needed to implement a thorough method that uses a percentage of random data used in the generation of the FISs and a percentage of real tested data. These two samples of data will be a better set of data to test during evaluation with a confusion matrix.

ACKNOWLEDGEMENTS

This work was supported in part by the Internal Fund for Research Projects (Grant No. 300.6.C.135.17) of the Autonomous University of Baja California, Mxico.

REFERENCES

Bezdek, J. C., Ehrlich, R., and Full, W. (1984). Fcm: The fuzzy c-means clustering algorithm. *Computers and Geosciences*, 10(2-3):191–203.

Bozkir, S. and Sezer, E. (2013). Fuat - a fuzzy clustering analysis tool. In *Expert Systems with Applications, FUZZYSS11: 2nd International Fuzzy Systems Symposium, vol. 40*.

Cai, A., Quek, C., and L., M. D. (2007). Type-2 ga-tsk fuzzy neural network. In *Evolutionary Computation. CEC 2007 IEEE Congress*.

Chai, W., Zhou, J., Chen, C., Nies, H., and Loeld, O. (2011). Continuous indoor localization and navigation based on low-cost ins/wi-fi integration. In *International Conference of Positioning and Indoor Navigation*.

Chiu, S. (1994). Fuzzy model identication based on cluster estimation. In *Journal of Intelligent and Fuzzy Systems, vol. 2*.

Crows, T. (1999). *Introduction to Data Mining and Knowledge Discovery*. Two Crows Corporation.

Dey, A. (2001). Understanding and using context. *Personal and Ubiquitous Computing*, 5(1).

Han, J. and Kamber, M. (1998). *DataMining: Concepts and Techiques*. Morgan Kaufmann, 2nd edition.

Hwang, S. and Donghui, Y. (2012). Gps localization improvement of smart- phones using built-in sensors. *nternational Journal of Smart Home*, 6.

Jang, J., Sun, C., and Mizutani, E. (1997). *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence. MATLAB Curriculum Series.* Prentice Hall.

Navarro, E., Peuker, B., and Quan, M. (2011). *Wi-Fi Localization Using RSSI Fingerprinting*. PhD thesis, Computer Engineering Department.

Ren, Q., Baron, L., and Balanzisnki, M. (2006). Type-2 takagi-sugeno-kang fuzzy logic modeling using subtractive clustering. In *Fuzzy Information Processing Society. NAFIPS 2006. Annual meeting of the North American*.

Sanchez, L., noz, L. M., Galache, J., Sotres, P., Santana, J., and Gutierrez, V. (2014). Smartsantander: Iot experimentation over a smart city testbed. *Computer Networks*.

Vaidehi, V., Monica, S., Saafer, S. S., Deepika, M., and Saangeetha, S. (2008). A prediction system based on fuzzy logic. In *Proceedings of the World Comgress on Engeineering and Computer Science, WCECS 2008*.

Yin, X. F., Khoo, L. P., and Chong, Y. T. (2013). A fuzzy c-means based hybrid evolutionary approach to the clustering of supply chain. *Computers and Industrial Engineering*, 66(4):768–780.

Ying, H., Ding, Y., Li, S., and Shao, S. (1998). Typical takagi-sugeno and mamdani fuzzy systems as universal approximators: Necessary conditions and comparison. In *Fuzzy Systems Proceedings, 1998. IEEE World Congress on Computational Intelligence. The 1998 IEEE International Conference Vol 1*.

Zadeh, L. (1965). Fuzzy sets. *Information and Control*, 8(3):338–353.