Automatic Generation of Fuzzy Membership Functions using Adaptive Mean-shift and Robust Statistics

Hossein Pazhoumand-Dar, Chiou-Peng Lam and Martin Masek
School of Computer and Security Science, Edith Cowan University, Perth, Australia

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Abstract: In this paper, an unsupervised approach incorporating variable bandwidth mean-shift and robust statistics is presented for generating fuzzy membership functions from data. The approach takes an attribute and automatically learns the number of representative functions from the underlying data distribution. Given a specific membership function, the approach also works out the associated parameters. The investigation here examines the application of approach using the triangular membership function. Results from partitioning of attributes confirm that the generated membership functions can better separate the underlying distributions when compared to a number of other techniques. Classification performance of fuzzy rule sets produced using four different methods of parameterizing the associated attributes is examined. We observed that the classifier constructed using the proposed method of generating membership function outperformed the 3 other classifiers that had used other methods of parameterizing the attributes.

1 INTRODUCTION

Eliciting representative membership functions (MFs) for data is one of the fundamental steps in applications of fuzzy theory as the success of many fuzzy approaches depends on the membership functions used. However, there are no simple rules, guidelines, or even consensus among the community on how to choose the number, type, and parameters of membership functions for any application or domain (Medasani et al., 1998). Several methods for the automatic generation of MFs have been proposed in the literature and the choice of function has been linked to the problem and the type of data available. However, in most of these techniques, the number of fuzzy sets has to be provided empirically. Furthermore, the range for membership functions generated by many existing techniques does not address the impact of outliers and noisy measurements in data.

In this paper, we propose a hybrid approach that incorporates variable bandwidth mean-shift (VBMS) and robust statistics for automatic generation of representative MF(s) for an attribute. The analysis of the underlying data distribution is unsupervised as the proposed approach first determines the number of modes from the probability density function (PDF) and then uses this value as the number of clusters for a multimodal data distribution. The approach overcomes the problems associated with some of the existing approaches by

- determining the number of representative MFs for the attribute from the underlying data distribution automatically
- automatically handling noise and outliers in the attribute feature space

The rest of this paper is organised as follow: Section 2 briefly reviews relevant literature on MF generation techniques. Some preliminary concepts are described in Section 3. Section 4 describes the proposed approach. The experimental evaluation of our technique is presented in Section 5 followed by conclusions and future directions in Section 6.

2 BACKGROUND

Many techniques have been proposed to generate fuzzy membership functions from an attribute. Three questions that have to be addressed are: (1) number of fuzzy sets to be defined for the dataset, (2) shape of the membership functions, and (3) parameters defining each membership function.

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Typically, techniques have used manual partitioning of attributes, mostly based on expert knowledge, and adopted a pre-determined number of membership functions (Seki, 2009) to partition the data space for the attribute by (usually evenly-spaced) MFs. However, manual approaches suffer from the deficiency that they rely on subjective interpretations from human experts.

Given a labelled dataset, evolutionary methods can also be utilized to generate MFs. Moeinzadeh et al., (2009) applied Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) for the adjustment of MF parameters to increase degree of membership of data to their classes for classification problems. Authors in (Amaral and Crisóstomo, 2001) applied GA for evolving parameters associated with MFs in a fuzzy logic controller for a helicopter. Initial guesses for the MFs are made by the expert and the GA adjusts the MF parameters to minimise the movement of a hovering helicopter. In the classification method proposed by Tang et al. (2014), a fitness function quantifies how well the crisp values of attributes are classified into MFs and the GA process evolves over time by searching the best set of MF parameters which optimises result of the fitness function.

Takagi and Hayashi (1991) also proposed the use of artificial neural networks (ANN) for the construction of membership functions. Their approach takes raw data (say, in a control problem), apply a conventional clustering algorithm to group the data into clusters and apply an ANN to this clustered data to determine the membership of a pattern within particular fuzzy sets.

However, for situations where the training data is not labelled, MF generation techniques generally involve unsupervised clustering of data using a specific distance measure and then the parameters of detected clusters (mean, variance, etc.) are used to generate MFs. For example, techniques (Pazhoumand-Dar et al., 2015) have used the Fuzzy C-Means (FCM) clustering algorithm (Kuok et al., 1998) to cluster a particular attribute into specific number of clusters. Cluster boundaries and the location of the centre were then used to determine the cluster membership function parameters. Doctor et al., (2014) presented a fuzzy approach to model an occupant behaviour in a residential environment. They used a Double Clustering technique (Castellano et al., 2002) combining FCM and agglomerative hierarchical clustering for extracting a predefined number of MFs from the user's recorded input/output data.

The disadvantage associated with most of these methods is that the number of fuzzy sets must be predefined. However, we usually do not know an optimal number of representative MFs for a particular attribute. In addition, outliers in data are included in range of MFs generated by many of these techniques. New robust techniques that can determine number of representative MFs automatically would address some of these limitations.

3 PRELIMINARY CONCEPTS

This section provides a review on related techniques and concepts used in the proposed approach. The variable bandwidth mean-shift strategy is first described, and is then followed by a review of the skewness adjusted boxplot technique.

3.1 Variable Bandwidth Mean-Shift Algorithm

VBMS proposed by Comaniciu et al., (2001) is a nonparametric clustering technique which does not require the number of clusters to be defined. It takes multidimensional data with an unknown density f and estimates the density at each point by taking the average of locally-scaled kernels centered at each of the data points, and tries to map each data point to its corresponding mode. The output of this technique is locations of modes detected in f and the cluster of data associated with each mode. Usually the kernel K is taken to be a radially symmetric, nonnegative function centered at zero such that $K(x) = k(\|x^2\|)$.

More specifically, given the data points x_i $(i = 1, \ldots, N)$, steps for the VBMS algorithm are as follows:

1. Use the plug-in rule (Sheather and Jones, 1991) to find an initial bandwidth h_0 for the kernel $K(x)$ and estimate PDF of data using Eq. (1).

$$\bar{f}(x) = \frac{1}{nh_0} \sum_{i=1}^{N} K(\frac{x - x_i}{h_0}) \tag{1}$$

Plug-in rule is a bandwidth selection technique for kernel density estimation of a data distribution. It involves using a kernel function to estimate the PDF of data. Estimation is performed per different values for the bandwidth of the kernel function, and the bandwidth that minimises an error function is selected.

2. Obtain $\lambda = e^{\frac{1}{N}\sum_{i=1}^{N} \log (\bar{f}(x_i)}$
3. Compute the adaptive bandwidth $h(x_i)$ for each data point x_i using Eq. (2).

$$h(x_i) = h_0[\frac{\lambda}{\bar{f}(x_i)}]^{1/2} \tag{2}$$

In Eq. (2), h_0 is a fixed bandwidth obtained from the plug-in rule (in step 1) and λ is a proportionality constant which divides the range of density values into low and high densities. When the local density for a given data point x_i is low (i.e., $\bar{f}(x_i) < \lambda$), $h(x_i)$ increases relative to h_0 implying more smoothing in the estimated density for the point x_i. For data points where their estimated density $\bar{f}(x_i)$ is greater than λ the bandwidth becomes narrower.

$$m(x) = \frac{\sum_{i=1}^{N} \frac{x_i}{h_i^{d+2}} g\left(\left\|\frac{x - x_i}{h_i}\right\|^2\right)}{\sum_{i=1}^{N} \frac{1}{h_i^{d+2}} g\left(\left\|\frac{x - x_i}{h_i}\right\|^2\right)} \tag{3}$$

where d is the dimension of the data and $g(x) = -k'(x)$

4. Choose the location of an unprocessed data as the initial location of the kernel and compute mean shift vector represented in Eq. (3) iteratively till convergence.
5. Record the location of kernel at convergence as the location of a mode of PDF, and group all data points covered by the kernel, during its successive locations, as the cluster associated with the mode.
6. Repeat step 4 to 5 until no unprocessed data is left.

More details on VBMS can be found in (Sheather and Jones, 1991).

3.2 The Skewness Adjusted Boxplot Technique

The skewness adjusted boxplot (SAB) technique is a graphical tool (with a robust measure of skewness) used in robust statistics (RS) for the purpose of outlier detection (Rousseeuw and Hubert, 2011).

Given a continuous unimodal data, SAB first calculates a robust measure of skewness (i.e., medcouple (MC) (Brys et al., 2004)) of the underlying data distribution. Then it outputs a normal range for the data which excludes possible outliers from the normal data.

More specifically, if x_n $(n = 1, \ldots, N)$ is a univariate data, medcouple (MC) of data is calculated as

$$MC = \underset{x_i \le m_n \le x_j}{med} h(x_i, x_j) \tag{4}$$

where for all $x_i \neq x_j$ the kernel function h is given by:

$$h(x_i, x_j) = \frac{(x_j - m_n) - (m_n - x_i)}{x_j - x_i} \tag{5}$$

In Eq. (5), m_n is the median of data points. If $x_i = x_j = m_n$, let $m_1 < \ldots < m_k$ be the indices of the data points which are associated with the median m_n. The kernel h is then defined as Eq. (6).

$$h\left(x_{m_i}, x_{m_j}\right) = \begin{cases} +1, & if\ i+j-1 < k \\ 0, & if\ i+j-1 = k \\ -1, & if\ i+j-1 > k \end{cases} \tag{6}$$

In case the distribution is skewed to the right, MC gets a positive value up to +1. MC becomes negative (up to -1) in a left-skewed distribution. Finally, a symmetric distribution has a zero MC.

Once the value of MC is obtained for the data, *SAB* calculates the normal range (*NR*) for the data as

$$NR = \begin{cases} [Q_1 - 1.5\, e^{(-4MC)}\ IQR; Q_3 + 1.5\, e^{(3MC)} IQR] & \text{if } MC \le 0 \\ [Q_1 - 1.5\, e^{(-3MC)}\ IQR; Q_3 + 1.5\, e^{(4MC)} IQR] & \textit{otherwise} \end{cases} \tag{7}$$

where Q_1 and Q_3 are the first and the third quartiles of the data and $IQR = Q_3 - Q_1$. For a left-skewed distribution (with a MC <0), the cut-off interval for the distribution will be the upper range shown in Eq. (7). The lower range in Eq. (8) is for right-skewed distributions having a positive MC.

Once *NR* is determined for the distribution, all observations outside the interval will be marked as potential outlier. Note that by using different ranges for different types of skewed distributions, we allow the cut-off interval to be asymmetric around the median of distribution.

4 THE PROPOSED APPROACH

The proposed approach takes an attribute and automatically defines a number of associated MFs as linguistic variables. Let an attribute take a series of crisp numerical values x_n $(n = 1, \ldots, N)$ and these data points belong to an unknown probability density function (PDF) *f*. The two-step procedure of the proposed approach for generating MFs for the attribute is as follows

Step 1. use VBMS to find modes (local maxima) of f representing the attribute and cluster of data points associated with each mode

Step 2. use skewness adjusted boxplot technique (Hubert and Vandervieren, 2008) to obtain the normal range of data for each cluster (where there are no outliers), and accordingly define a MF for the cluster.

The output of Step 1 is the location of modes of f denoted as $m_{i\,(1 \leq i \leq N)}$ and the cluster of data associated with each mode.

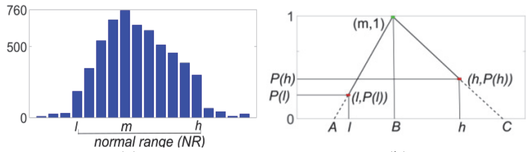
When an attribute has a multimodal PDF and each mode may be associated with a different density distribution, one fixed global bandwidth is not optimal for estimating the location of modes in PDF, and thus local bandwidths should be computed (Comaniciu et al., 2001). Using VBMS, we determine a local bandwidth for each data point in a way that points corresponding to tails of the data distributions receive a bigger bandwidth than data points lying in large density region of distributions and hence the estimated density function for tails of the distributions is smoothed more.

In Step 2, we use the output from Step 1, the number of modes as the number of required MFs representing the attribute and for each cluster of data associated with a mode, we define a MF. We first use the SAB technique to determine the normal range (*NR*) for the cluster (see Section 3.2) and we denoted this as $[l, h]$.

The output of Step 2 for each attribute is a tuple (X, m_1, m_2, … , m_{nc}) as linguistic variables, where X stands for the attribute name and m_i stands for an MF defined over the universe of discourse for the attribute and *nc* stands for the number of modes identified in Step 1.

Various forms of MFs, together with their corresponding parameters, can be used in the proposed approach to characterise the identified clusters. In this paper we first explored using triangular membership functions (TMFs) because of their simplicity of calculation and ability to represent skewed distributions. As shown in Figure 1(b), parameters of TMF are defined by a triad (A, B, C), with point A representing the left foot of TMF, B is the location of the center, and C is the location of the right foot.

To define a TMF for a detected cluster we use *NR* $[l, h]$ (l is the lower and h is higher limit for the normal range, respectively) associated with the cluster, and the cluster mode, m, to determine its parameters (A, B, C). This is illustrated using an example shown in Figure 1.



(a) (b)

Figure 1 (a): The histogram of a detected data cluster from Step 1. The vertical axis shows the number of observations. (b) The corresponding TMF defined for the cluster.

Figure 1(a) showed the histogram associated with the cluster, with the detected mode m and normal range $[l, h]$ shown, in Figure 1 (a). A probability density distribution (PDF) is first obtained from this histogram. Figure 1 (b) shows the corresponding TMF defined for the cluster with m as the center point B for the TMF. Next, using the generated PDF, we calculate the probability density of lower bound (l) and higher bound (h) of the cluster, denoted by $P(l)$ and $P(h)$ in Figure 1(b), respectively. Then, we find the parameter A for the TMF by extrapolating the two points (m, 1) and (l, $P(l)$). In the same manner, we find the parameter C by extrapolating the two points (h, $P(h)$) and (m, 1). Now, TMF is defined using Eq. (8).

$$\mu^i(x) = \begin{cases} 0 & if\ x \leq A_i \\ \dfrac{x - A_i}{B_i - C_i} & if\ A_i < x \leq B_i \\ \dfrac{C_i - x}{C_i - B_i} & if\ B_i < x \leq C_i \\ 0 & if\ C_i \leq x \end{cases} \tag{8}$$

Figure 2 (a) and (b) shows examples of histograms for attributes with a unimodal and bimodal distributions, respectively. Each distribution of data associated with a detected mode is shown with a different colour. In case of Figure 2 (a), VBMS associates all the data pints with the only mode detected in the PDF whereas for Figure 2 (b), two separate distributions as shown in blue and red colours have been detected. The corresponding normal range and the location of mode detected for each of the distributions in Figure 2 (a) and (b) are shown in Figure 2 (c) and (d), respectively. In Figure 2 (c), the detected lower and upper bounds for the distribution are shown by the two vertical black lines, respectively, and the range between these two lines forms the normal range for the cluster associated with the distribution. All the data points shown by the red dots outside the detected normal range are marked as outlier. As can be observed from Figure 2 (c), the distance of the lower limit to the mode of distribution is larger than that between the mode and the upper limit, thus reflecting the

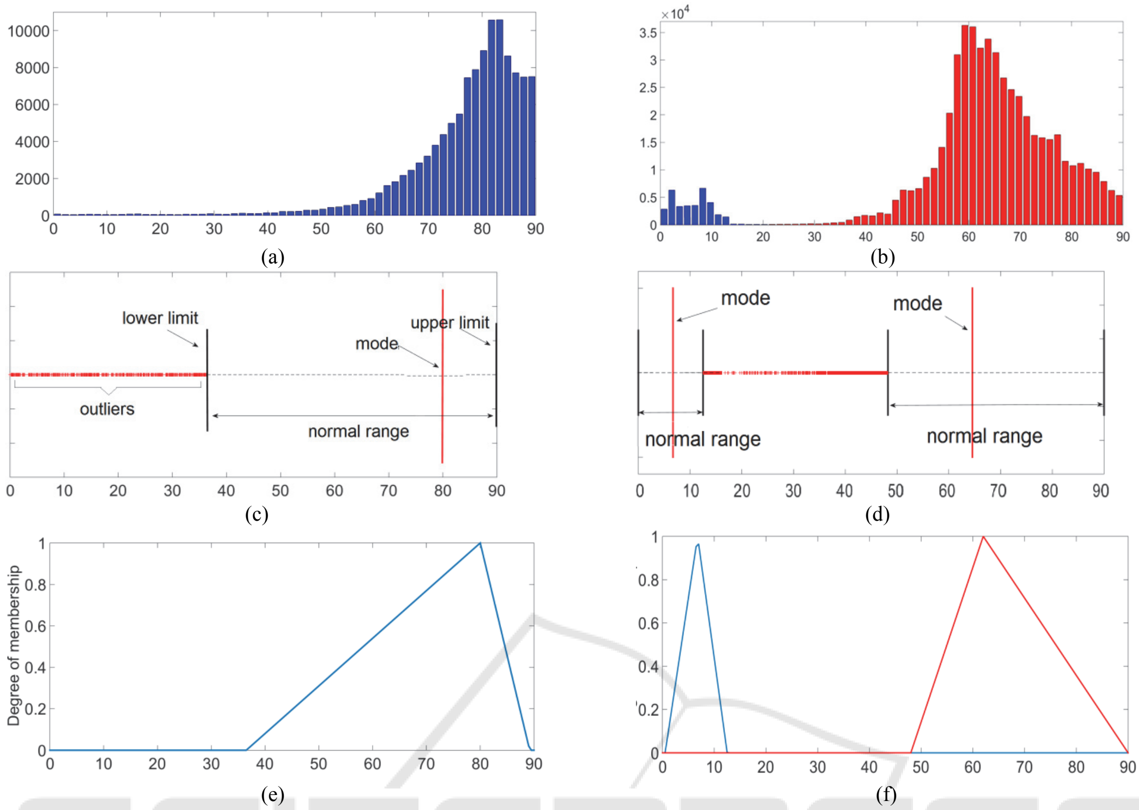


Figure 2 (a) and (b): examples of attributes with a unimodal and bimodal distributions, respectively. (c) and (d) the corresponding normal range and the location of mode detected for each of these distributions, respectively, and (e) and (f) the corresponding TMFs.

skewness of the underlying distribution in Figure 2 (a). In Figure 2 (c) and (d), the data points inside each normal range are kept as a cluster, and data points that are outside of the detected normal ranges are considered in this technique as being outliers and will be eliminated. Figure 2 (e) and (f) show TMFs representing the distributions in Figure 2 (a) and (b) obtained from the procedure described in Step 2 of the proposed approach.

5 EXPERIMENTAL RESULTS

Our evaluation consists of comparison between the proposed approach and two other techniques in terms of (i) parameterising MFs for attributes with different distributions, and (ii) classification performance of a fuzzy rule set that was developed using the parameterised output of each of the 3 techniques.

5.1 Dataset

We evaluated the effectiveness of the proposed approach using attributes associated with a dataset for classification activities of daily living (ADLs), as previously used in (Pazhoumand-Dar et al., 2015). This dataset is collected via multiple Kinect cameras, each installed in a different area of a single monitored house. Data was collected from this house for a period of five weeks, during which a single occupant undertook activities typical of a retired elderly person. From each Kinect, observations for activities undertaken are taken at one-second intervals and ones in which a person is detected are stored. The entire dataset consisted of more than two million observations. The attributes we extracted from this dataset were the occupant's Centre of Gravity pixel location (Xc, Yc), Aspect Ratio (AR) of the 3D axis-aligned bounding box, and Orientation (O).

The dataset for each location was partitioned into a training set and an unseen test set. The training set for each location consisted of nearly one million observations of behaviour patterns associated to typical (or normal) ADLs of the occupant. The test set holds some sequences of normal behaviour (i.e. typical ADLs) and abnormal events (e.g. occupant lying on the floor of the kitchen).

The system used for the gathering of data consisted of Windows 8.1 notebook PCs, with one notebook per Kinect device. Custom data collection code was written in C# under the Microsoft .Net framework. Data analysis was subsequently performed in MatLab™.

5.2 Comparison of Techniques for Parameterizing Attributes with Different Characteristics

Attributes with different data distribution were used to compare the parameterisation results between the proposed approach (VBMS–RS) and two other techniques: (i) using MS (instead of VBMS) in Step 1 of the proposed approach followed by the procedure of robust statistics in Step 2 (MS-RS), and (ii) using the Fuzzy-C-Means (FCM) clustering algorithm to generate a fixed number of membership functions over the domain of a particular attribute without the use of robust statistics. For each particular attribute, we empirically set this number for FCM according to the number of modes in the attribute probability density function, as discussed in the following sections. In each case, comparisons are made through the clusters and TMFs produced by each of the 3 techniques.

5.2.1 Attribute with Separated Distributions

One example with separated distributions is for the attribute Xc associated with the living room dataset, as shown in Figure 3.

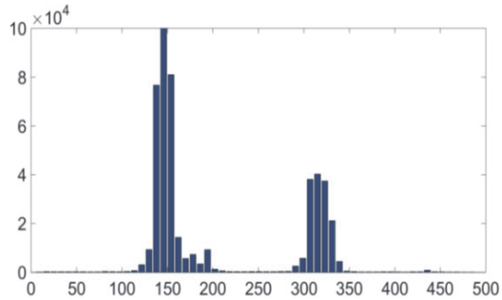


Figure 3: A bimodal distribution for the Xc attribute associated with the living room dataset.

The reason is that, as shown in Figure 4 (a) and (b), the living room was occupied mainly for sitting at a computer desk (the left distribution) and using the sofa for watching TV (the distribution to the right) and as a result, values for Xc are mostly concentrated around two separate regions in feature space of Xc (i.e., 150 and 325), respectively.

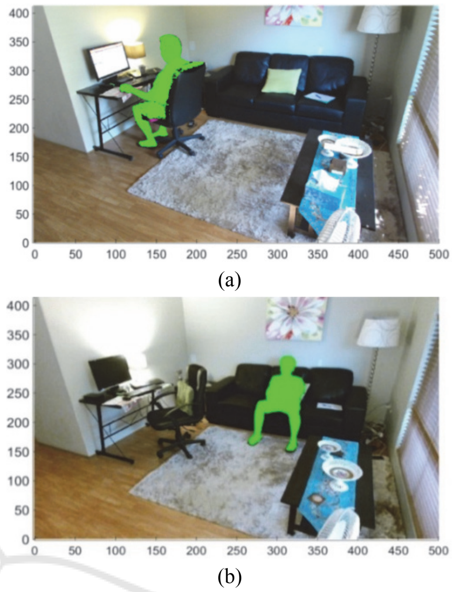


Figure 4: (a) Sitting at a computer desk, and (b) watching TV while sitting on a sofa in the living room. The body of the occupant is masked by its binary silhouette obtained from the Kinect SDK and the numbers in the vertical and horizontal axis indicate pixel location.

It should be remarked that all the attributes in this dataset were obtained from depth maps and their corresponding binary mask of the occupant. The colour images shown in Figure 4 are only to visualise the living room area for the readers and the attributes for the two observations shown in Figure 4 were actually obtained from the two depth maps shown in Figure 5, respectively.

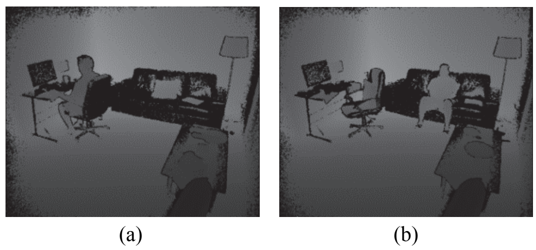


Figure 5: The corresponding depth maps of images shown in Figure 4.

Figure 6 (a) illustrates the results of using VBMS–RS for parameterising distributions of Xc from the living room. Each underlying distribution of data associated with a detected mode is shown with a different colour.

VBMS–RS could separate correctly this attribute feature space into two main underlying distributions. The distribution to the right in Figure 6 (a) is in the shape of reverse-J (skewed to the left), and the corresponding TMF defined by VBMS–RS represents only the range for the normal data points associated with this distribution.

To further evaluate VBMS-RS, we replaced VBMS with MS in Step 1 of the proposed approach and repeated the experiment. By comparing the results, we observed that where the distributions in the attribute feature space are separated distinctly, both methods work equally well. However, MS–RS requires an empirical input, the bandwidth parameter, whereas for VBMS in the proposed approach, the initial bandwidth is derived from the data automatically (see Section 3.1).

In the comparison using FCM, we empirically set the number of membership functions to be 2 (as this is obvious from a visual examination of the data). As shown with blue and red colours, Figure 6 (e) demonstrates that FCM correctly separated the attribute into two distributions in the attribute feature space. As a result, the two TMFs in Figure 6 (f) were generated to represent the two distributions detected in the attribute feature space, respectively. Since FCM does not use robust statistics, the resulting parameterization of the TMFs is not the same as the proposed approach. More specifically, TMFs generated by FCM have a wider support and hence represent a wider area outside the normal range for the two main distributions in Figure 6 (e). As a result, the TMFs generated by FCM will be representing many rare observations (outliers) around the main distributions. For example, they give membership values 0.17 and 0.83 to the outlier point (380) so that the sum of memberships of this point is one. This is in contrast to TMFs generated by VBMS-RS which give zero membership to this outlier point.

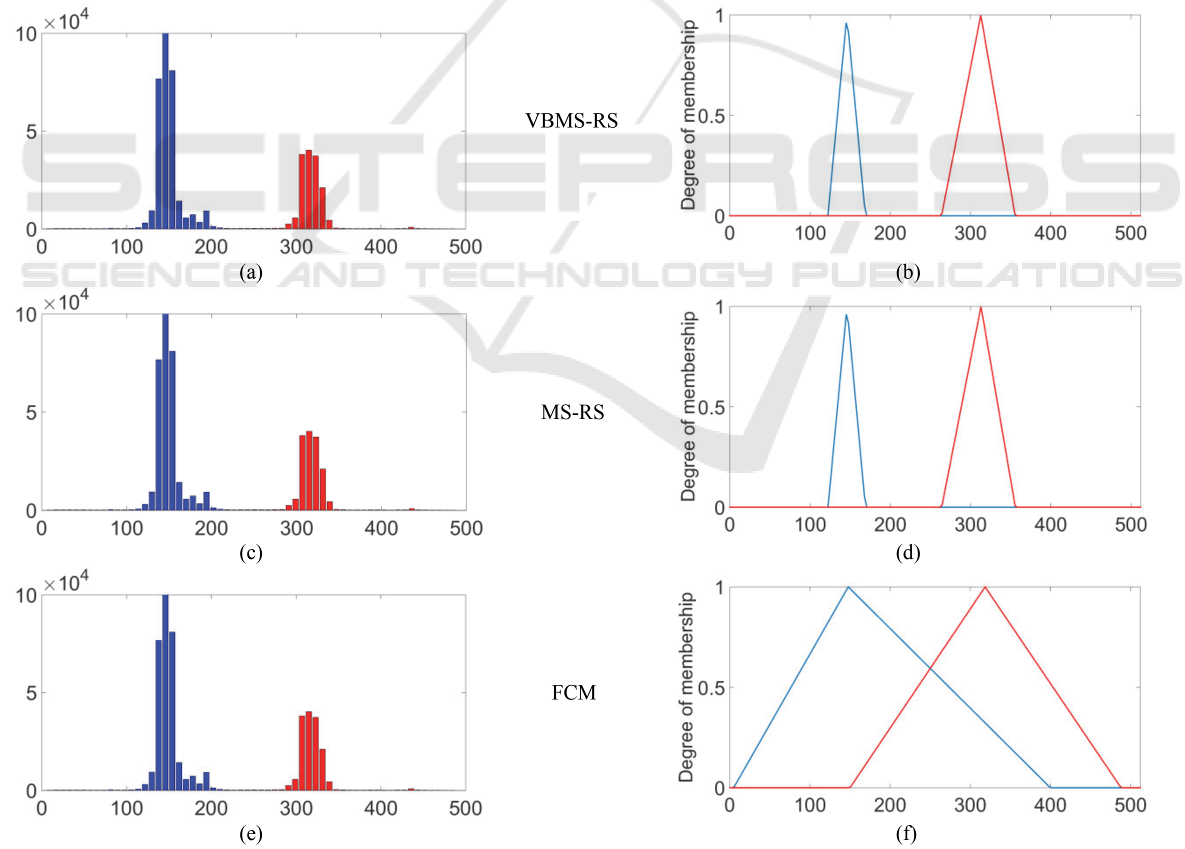


Figure 6: Different techniques for parameterising the two underlying distributions present in Figure 3. The different colors in each of (a), (b), and (c) show range for clusters obtained using the 3 different techniques. (b), (d), and (f) show the corresponding TMFs.

5.2.2 Attribute with a Unimodal Distribution

One example of the attributes that have unimodal skewed distribution is the *AR* attribute from the dining room, as illustrated in images on the left hand side of Figure 7 (i.e., 7 (a), 7 (c), and 7 (e)). The overall distribution shown in those images illustrates the skewed distribution for *AR*. Different colors in each of the images indicate the distributions related to the clusters that have been obtained using the 3 different techniques. Figure 7 (b), (d), and (f) show results of generating TMFs for the distribution of the *AR* attribute using the 3 different techniques. As shown in Figure 7 (a), VBMS-RS correctly associated all data points with the only mode in the distribution. However, as shown in Figure 7 (c), MS-RS has broken the distribution into two clusters. This difference is mainly because in VBMS, points that correspond to the tails of the underlying density will get a broader neighbourhood and a smaller importance. So, they will be included to main structures and hence, tail of distributions will not be broken into pieces. This is unlike MS, where it assigns a fixed global bandwidth to all data points and hence all points receive the same importance when estimating the PDF of data.

As the distribution is unimodal, input value for the number of clusters in FCM was set to 1. From Figure 7 (e) we can see that although FCM has grouped all data points in the distribution into the stipulated one cluster, the support of the generated TMF in Figure 7 (f) is much broader than TMF generated by VBMS-RS which might lead to non-specific responses for classification of the attribute values (i.e., every point is considered to be in the set). Also, when the application of generating TMFs is for classification of outliers, the generated TMF in this example is representing many rare observations (outliers) located between 4 and 6, and hence will be not able to correctly classify a new abnormal observation within that boundary.

However, the TMF resulted from the proposed approach is not representing any data point for outside the normal range [0.5 , 3.5] and therefore, VBMS-RS method can obtain better classification results for normal points and better accuracy for handling outlier observations.

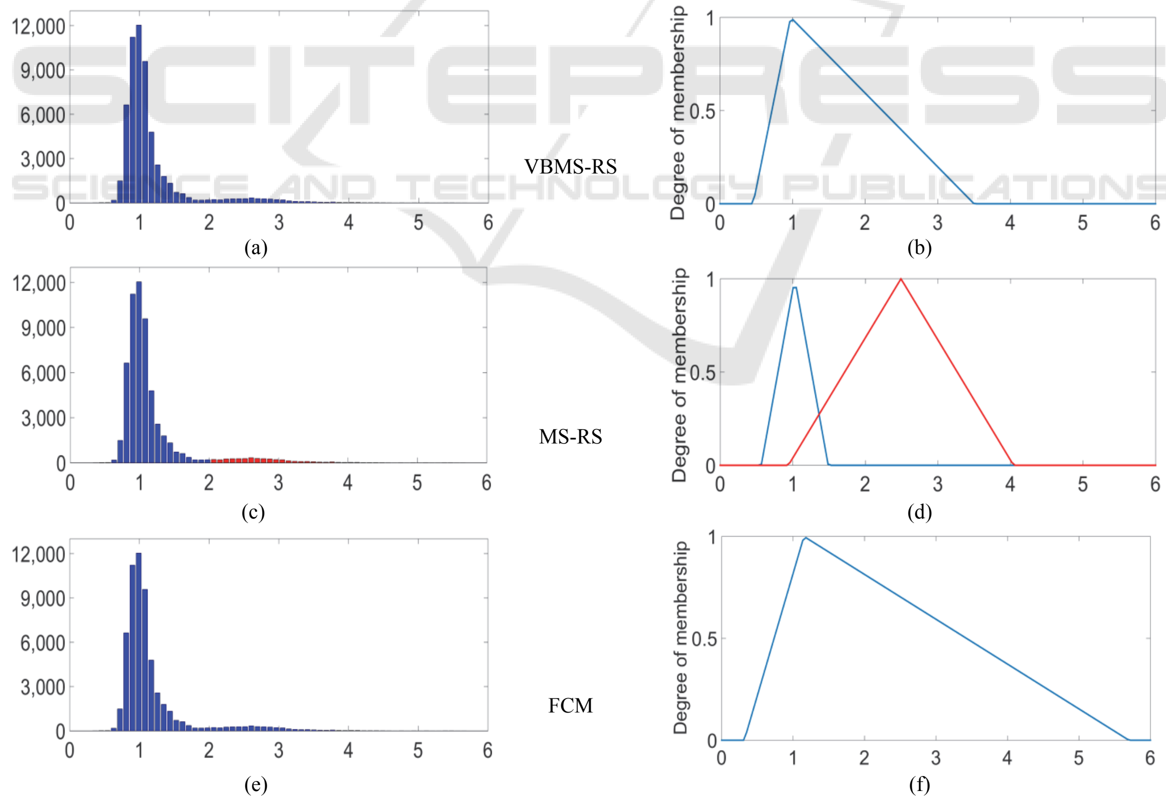


Figure 7: Using the 3 different techniques for parameterising distribution of the AR attribute for the dining room dataset. (a), (c), and (e) show the range for clusters obtained using the 3 different techniques, and (b), (d), and (f) show the corresponding TMFs.

5.2.3 Attribute with Multimodal Distribution

An example of an attribute with multimodal distribution is *Xc* from the kitchen dataset. From the ground truth in examining the video data for this attribute there were three distinct places for *Xc* where the occupant performed most of the activities in the kitchen. As a result, PDF for this attribute has 3 modes, each associated with a particular distribution and the 3 distributions overlap.

Results of parameterising this attribute using the 3 different techniques are shown in Figure 8. Input value for the number of clusters to be created by FCM was set to 3. It is clear from the results in Figure 8 that, VBMS-RS partitions the feature space into the right number of membership functions whereas using MS-RS and FCM were unable to separate the mixed distributions correctly. The difference between results for VBMS-RS and MS-RS is due to the fact that, using VBMS, the data points lying in large density regions will get a narrower neighbourhood since the kernel bandwidth is smaller, but are given a larger importance. So when main distributions are mixed in the attribute feature space, VBMS can better separate those structures than MS. This finding is consistent with Comaniciu et al., (2001).

From Figure 8 (f) FCM has partitioned the attribute feature space to be represented by three TMFs. However, the parameters for these three TMFs are different to those of the results from VBMS-RS. The reason is that FCM aims to minimise the distance of data points from their respective cluster centres. As a result the locations of centre of clusters are not always corresponding to the modes in distribution of data. Furthermore, as seen in Figure 8 (e), distributions with their modes located on pixel location 150 and 200, respectively, are represented by the same TMF. Hence, TMFs generated by this technique are not accurately representing data distributions in this attribute feature space.

5.3 Results on Classification Accuracy using TMFs Produced by Different Techniques

The characteristics of MFs generated by a particular technique have a direct impact on performance of the corresponding fuzzy rule set for classification purposes. In other words, a better technique to estimate the underlying distributions for attributes can lead to more representative MFs and hence a better classification accuracy of the corresponding fuzzy rule set. To investigate this, we conducted experiments in which we applied the output of the 3 different MF generation techniques, including the proposed approach, to obtain a fuzzy rule set for the application of detecting abnormal activities in ADLs. As we had data from 5 rooms and each room was associated with 4 attributes with different number of modes in their corresponding PDF, we empirically set the number of clusters for FCM to a specific number (i.e., 3) to suite across all situations, a technique used typically by existing fuzzy approaches (Tajbakhsh et al., 2009). To obtain the classifier, we extracted the attributes (described in Section 5.1) from the training dataset associated with each location and developed the fuzzy system using the approach from (Pazhoumand-Dar et al., 2015). A brief description of this approach is described below:

The unsupervised ADLs monitoring approach proposed by (Pazhoumand-Dar et al., 2015) uses a set of attributes derived from Kinect camera observations and consists of two phases: training and monitoring.

During the training phase, the system first learns “normal” behaviour patterns of the occupant as a set of fuzzy rules. For each monitored location, normal behaviour patterns are learnt by finding frequent occurrences of attributes via the use of a fuzzy association rule mining algorithm (Kuok et al., 1998). The antecedent part of each rule in the resulting fuzzy rule set for each monitored location represents a combination of fuzzy linguistic values describing a frequent behaviour of the occupant. The normal duration of that frequent behavior is shown in the consequent part of the rule.

The monitoring phase takes the fuzzy rule set obtained from the training phase as input, and for each location, it classifies the current behaviour of the occupant as abnormal if it is not in the set of frequent behaviours. For more detail, we refer the reader to (Pazhoumand-Dar et al., 2015).

Table 1 compares classification accuracy for fuzzy rules obtained using the output of the 4 different MF generation techniques. More specifically, 40 sequences of different scenarios for normal and abnormal behaviour in the unseen test set (20 sequences for each category of normal and abnormal behaviour, respectively) were used to evaluate the accuracy of the fuzzy rule set obtained using the output of a particular technique and the resulting classification accuracy is reported in Table 1.

From Table 1 it can be observed that when we use MS-RS to obtain TMFs for fuzzy rules, 6 of the test sequences, mostly representing an abnormal behaviour, were classified incorrectly. This is mainly because MS couldn't distinctly separate overlapped distributions in feature space of attributes. Therefore, for some attributes two or more behaviour patterns belonging to different overlapped distributions were represented by the same TMF and hence represented by the same fuzzy rule. For example, distributions of *AR* for crouching on the kitchen floor (to pick up an object) and bending down (to manipulate objects inside the kitchen cabinet), while belonging to different main distributions in the attribute feature space, considered as belonging to the same cluster, and hence, the corresponding fuzzy rule set was not able to label a sequence for spending a long time sitting on the kitchen floor as abnormal behaviour.

Classification that results from using FCM to generate TMFs produced accuracy of 78%. This is mostly because the test sequences involving normal behaviour patterns that were slightly different from their corresponding training patterns were misclassified by this classifier as abnormal. This was mainly because FCM broke main distributions for some attributes into pieces and consequently, for a particular activity, when most of training values belonged to a particular part of the distribution and the values for test sequences fell into another part of the distribution, the corresponding fuzzy rule for the activity could not be able to trigger and hence less accuracy of the classifier.

We also evaluated the classification accuracy of the fuzzy rules obtained by applying the proposed approach without robust statistics and results are shown Table 1 denoted by VBMS. We observed that many test sequences for abnormal behaviour have been labeled as normal. In those sequences, the values of attributes were well outside of the normal range for the main distributions in the feature space of attributes. However, since the range of generated TMFs was wider than the range of main distributions, they included many outlier observations, and hence, outlier observations in each of those test sequences triggered a corresponding rule for a normal behaviour in the rule base to be

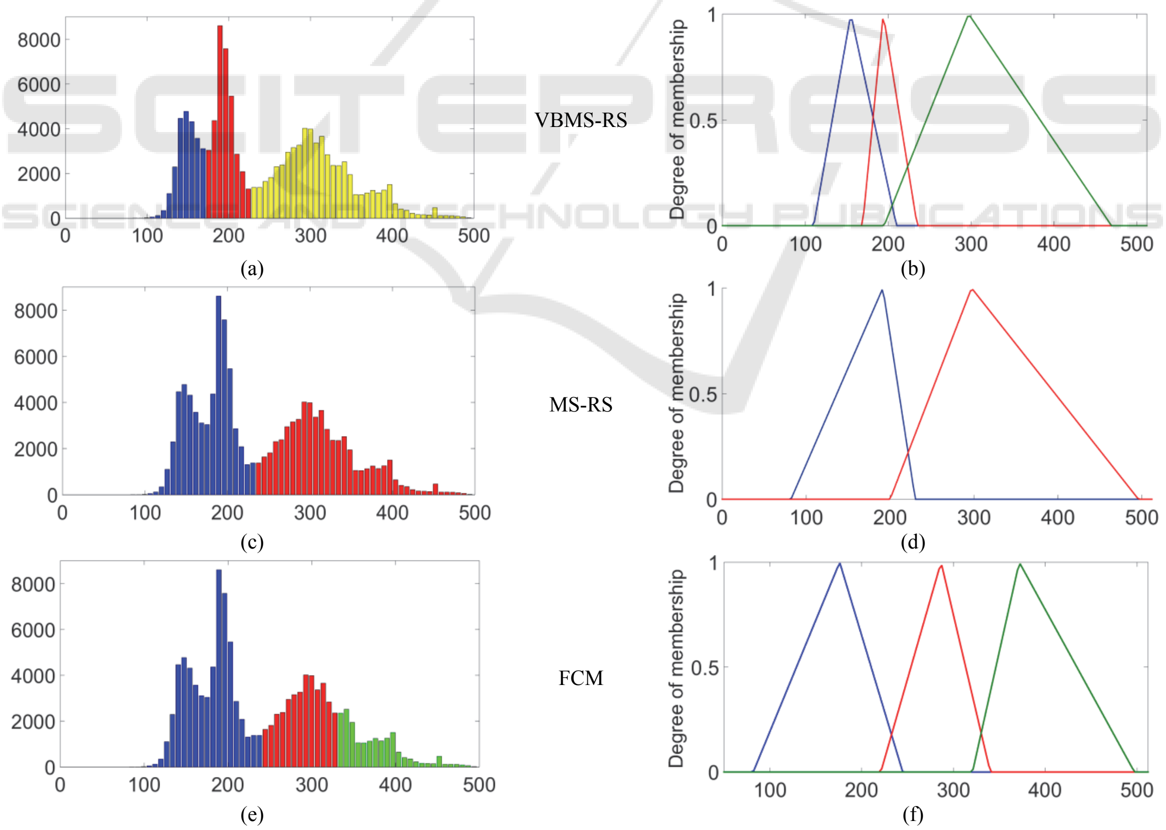


Figure 8: Results for using the 3 different techniques for parameterising distribution of Yc associated with the kitchen dataset. (a), (c), and (d) show the range for clusters obtained using the 3 different techniques, and (b), (d), and (f) show the corresponding TMFs.

fired and resulted in the test sequence being labelled normal.

Table 1: Results of using the output of different MF generation techniques to obtain a fuzzy rule set for the application of detecting abnormal activities in ADLs.

Method	Normal behaviour	Abnormal behaviour	Overall accuracy
FCM with 3 clusters	70%	85%	78%
MS-RS	90%	80%	85%
VBMS	100%	35%	68%
VBMS-RS	100%	85%	92.5%

From the last row of Table 1 we see that the rule set obtained from the results of VBMS-RS could classify 37 test sequences correctly and hence an accuracy of 92.5%. We observed that for almost all attributes, using the combination of VBMS and robust statistics yields in the resulting TMFs representing only the normal range for the main distributions in the attributes. Therefore, while outlier observations for abnormal behaviours were classified correctly, attribute values during most of sequences for normal behaviour were within the bounds associated with the generated TMFs, and hence, those sequences triggered a rule corresponding to a normal behaviour to fire.

6 CONCLUSIONS

In this paper, we presented an unsupervised MF generation method which learns the number of representative MFs for a dataset from the underlying data distribution automatically and sets up parameters associated with each MF. We performed comparisons between the results of the proposed approach and other techniques. In term of partitioning a particular attribute, results confirmed that the proposed approach generates membership functions that can separate the underlying distributions better. In comparing the results of different parameterization techniques in building fuzzy rules for classification of ADLs, we observed that the proposed approach allows us to achieve a better classification accuracy, thus showing a better performance for the proposed approach. Future work will involve extending the approach to address different types of membership functions.

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