Abstract

In the two-level weighted variable clustering method, weights variable and weight view are used to identify the important variables in each view, and identify compact cluster structures within these views respectively. If the view has dense cluster structures, a large view weight is allocated so as to enhance the effect of such view and vice versa. In the two-level variable weighting method, the view weights will be only determined in the view level, whereas the variable weights will be only determined in a view. Therefore, the two levels of variable weights will eliminate the unbalanced phenomenon and compute more objective weights. In this dissertation, a novel recursive three tier fuzzy K-means algorithm has been proposed which use TW-k-means with two-level variable weighting clustering algorithm for clustering of multi view data is presented which encapsulate Karcher expectation estimator for symmetric positive definite (SPD) matrix-variant random variables and at last apply fuzzy approach r, fuzzy k-means provides the flexibility to employ different fuzzy membership function to measure the distance between multi view data. Recursive algorithm for estimating the Karcher expectation of an arbitrary distribution estimates computed by the recursive algorithm asymptotically converges in probability to the correct Karcher expectation. The steps in the recursive algorithm mainly consist of making appropriate moves on geodesics the algorithm is simple to implement and it offers a tremendous gain in computation time of several orders of magnitude over existing non-recursive algorithms.

1. Introduction

Multiview data are instances that have multiple views (representation/variable groups) from different features spaces. It is the result of integration of multiple types of measurements on
observations from different perspectives and different types of measurements can be considered as different views.

Data mining [1] operated from a large data sets of implicit non-trivial extraction of novel, and knowledge is an evolving technology that is a direct result of the increasing use of computer databases to store and retrieve information efficiently. It also known as Knowledge Discovery in databases (KDD) and allows data extraction, data analysis and data visualization of large databases on a high level of abstraction, without any specific course in mind. The work of data mining is heard by a modeling method called him to make predictions. Data mining techniques are the result of a long process of research and product development, including artificial neural networks, decision trees and genetic algorithms. This data recovery if needed and contributes to data extraction technology. Data mining can be considered as a result of the natural evolution of information technology. This technology provides high availability of large amounts of data and the imminent need to turn data into useful information and knowledge. Data mining is the extraction of knowledge patterns or large amount of interesting data. It may be known by different names, such as knowledge discovery (mining) in databases (DCE), knowledge extraction, data analysis / design, data archeology, the data dredging, information harvesting, intelligence business and more. The term "data mining" [2] is simply the analysis of data in a database using tools such as trends or anomalies without knowledge of the meaning of the data and is used mainly by statisticians, researcher’s databases and the business community. Data mining software is not limited to change the presentation, but discovers previously unknown relationships between data. The information in the process of data mining functions is contained in a historical database of past interactions. In principle, data mining is not specific to one type of media or data. Data mining should be applicable to any type of data warehouse.

Each transaction in the area of business is (often) "stored" in perpetuity. These operations are usually related to the time and can be inter-company and within the company effective use of data in a reasonable competitive decision making time is definitely the most important to solve the problem for companies struggling operating survive in a highly competitive world. Census data for staff and client files of government, very large collections of data is collected continuously in individuals and groups. This type of data often reveals whether the information is collected, used and even shared. When correlated with other data this information can shed light on the behavior of customers.

2. Clustering And Its Approach

No need to stress here the need for automated data analysis and extraction of information, it has become ubiquitous today. For data and designate facts. According Acko (1989) simply exists and has no significance beyond its existence (in itself). It may exist in any form, whether or not usable. It has no meaning in itself. Semantic data connections that give meaning: Data information is processed. The extraction of previously unknown and potentially useful information is the subject of implicit data mining field. Algorithmic framework to provide automatic support for data mining is usually called machine learning. The data are generally present in raw form: records called data elements are expressed in tuples (ordered sequences) of categorical numeric /; each value of the tuple indicates the observed value of a property. The characteristics of a data set are also known variables or attributes.
Information can be extracted automatically by searching for data models. The process of identifying patterns in the data is called learning from data. Depending on the type of task exploration of various data patterns can be identified. The extraction of association aims to detect an association between the characteristics for rules. Association rules usually involve non-numerical attributes; typical application is the analysis of the market basket in which items are items in shopping carts and partnerships between these purchases are sought. To predict the value of a nominal characteristic classification aims; property in question is called the class variable. The classification is called supervised because the apprenticeship system is presented with a series of small examples (the values of the class variable given) from which we expect to learn a way of classifying unseen examples learning. In numerical weather prediction to predict outcome is not a separate category but a numerical quantity.

Clustering is the task of identifying natural groupings in the data. Unsupervised learning is called, because even if the result is the prediction of a class variable, not of training examples provided. Cluster analysis is exploratory and descriptive. No templates or pre assumptions, but the goal is to understand the general characteristics or data structure.

Clustering is a division of data into groups of similar objects. Representing data by fewer clusters necessarily loses certain fine details, but achieves simplification. Data models by their groups. Data modeling puts clustering in a historical perspective rooted in mathematics, statistics and numerical analysis. On Machine Learning perspective clusters correspond to hidden structures, is the search for groups unsupervised learning, and the resulting system is a concept of data. From a combination of practical perspective plays an important role in exploration data applications, such as exploration of scientific data, information retrieval and text mining applications, spatial databases, Web Analytics, CRM, marketing, medical diagnostics, computational biology, and many others.

Clustering is the subject of active research in several fields such as statistics, pattern recognition and machine learning. This study focuses on clustering in data mining. Data mining adds to group the complications of very large databases with many attributes of different types. This imposes design requirements relevant clustering algorithms unique. A variety of algorithms have recently emerged that meet these requirements and successfully applied to data mining problems in real life. They are interviewed.

3. Multiview Clustering

Multiview data are instances that have multiple views (pictures / tag groups) of the various functional areas. It is the result of the integration of several types of measurements on observations from different points of view and different types of measures can be considered to be different opinions. For example, variables nucleated cell data [1] is divided for the density, geometry, "color" and texture, each representing a particular action to nucleated blood cells. In a data set of bank customers, the variables can be divided into a demographic view showing the customer demographics, a view that information on customer accounts in, and expenditures that describes the behavior of customer spending. Web pages can be represented with three views: a view expression vector whose elements correspond to the appearance of certain words in the text of the Web page, a graphic view showing links to other sites that each point of Web pages and a view of the term vector of words in the anchor text. In the last decade, data has sparked interest in grouping called Multiview [2], [3], [11]. Unlike traditional clustering methods that have multiple views as a
set of flat variables and does not take into account differences between the various points of view, multi-view clustering uses the information from multiple perspectives and to take differences between the different points of view into consideration in order to produce more accurate and robust data partition.

Clustering weighting variable was the subject of considerable research in cluster analysis [12], [13] a weight for each variable is calculated automatically and identify important insignificant variables and variable by variable weight. Multiview data could be considered as having two levels of variables. In the dataset of multiple views, the difference in perspectives and the importance of individual variables in each view must be taken into account. Traditional classification methods do not calculate variable weights for individual variables and does not take into account differences of views in data Multiview. Therefore, they are not suitable for the multi-frame data. To our knowledge, this is the first clustering algorithm SYNCLUS Multiview using variable weight weighting for the two points of view and different variables in the clustering process. [28] But the weight variables that are automatically calculated and light weights are given by users. Recently, Tzortzis and Likas [9] proposed a weighted combination of mixture models based on items (WCMM) that assigns different weights to the views and learn from these weights automatically, but his method does not take into account the varying weights. Both algorithms have a great weakness that does not adapt to large data sets.

There are two approaches to learning Multiview [10] centralized and distributed. Centralized algorithms make use of multiple representations simultaneously to uncover hidden trends in the data. Most existing work in the group follows the multiview centralized extensions to existing cluster algorithms [3] to [9]. Distributed algorithms grouped each from others first independent view using a unique algorithm for matching and combine individual classifiers to obtain a final score [10], [11]. Bickel and Scheffer [3] proposed the general algorithm based on the EM algorithm and co-developed an EM algorithm multinomial two of sight and a two-view spherical k-means algorithm Multiview MS. However, their methods cannot guarantee the convergence so that it is difficult for a user to decide when to stop. Kailing et al. [4] proposed a multi-view version of the DBSCAN algorithm. In their method, DBSCAN first used in each to produce a number of small groups and lots of noise. Then, the terminal groups were determined using the union and the intersection of neighborhoods. His [5] proposed an algorithm for spectral classification which requires two views that opinions are independent. His method is to group the data in each to minimize the disagreement between the groups in each view. Zhou and Burges [6] Multiview spectral classification by the generalization of the single, common standard to cut Multiview view. The multiview normalized find a cut that is close to the optimum in each graph cut, and can be optimized by a relaxation of the actual value. Relaxation leads to mix rational vertices of Markov chains associated with different graphics. Blaschko and Lampert [7] proposed a clustering algorithm for both points of view based on kernel canonical correlation analysis (CCA), called data correlation of the spectral classification. Separate measurements for each data representation of similarity are used for the projection of the data previously seen at a dealership. Chaudhuri et al. [8] clustering algorithm proposed that performs clustering on the lower dimensional multiple data views subspace, projected through the canonical correlation analysis. Two algorithms for blends and mixtures of Gaussian distributions developed concave folder. Long et al. [10] proposed a general model to bring under one multiview distributed framework. The proposed model introduced the concept of mapping function for different models from different areas of comparable models and thus an optimal model can be learned from the various models of multiple
viewpoints. Greene and Cunningham [11] proposed a set of data multiview clustering algorithm through an integration strategy later. In their method, a matrix containing the partition is created for each individual and then decomposed into two matrices using the matrix factorization approach: show the contribution of the partitions for the last groups with multiple displays, called target groups and other assignment of cases to target groups. Current methods for multi-view clustering both take multiple variables and individual viewpoints into consideration. However, most of them are extensions of the spectral classification for MS or not scalable to large data sets.

3.1 TW K-MEANS

TW K-means, a novel bivariate level weighting k-means algorithm for multi-view data. In the TW-k-means algorithm to distinguish the effects of different views and different grouping variables, the weights of views and different variables are introduced into the distance function. The weight of vision are calculated from integer variables, while the weights of the variables in a view are calculated from the subset of data that includes only the view variables. Therefore, light weights reflect the importance of the views of all data, while the variable weights reflect only a view of the importance of the variables in the view. An optimization model is presented for the k-means algorithm and enter TW derived model to calculate two weights of view and variable weight formulas. We define the TW-k-means algorithm as an extension of standard k-means of two additional process steps to calculate the weight variables and lightweight at each iteration. From both steps do not require intensive computation, the new clustering algorithm remains effective in view of wide high multidimensional clustering data. SYNCLUS report and WCMM, TW-k-means can automatically calculate two weights for individual variables and weight. In addition, a fast algorithm of classification which has the same computational complexity as k-means.

3.2 Variable Weighting Clustering

Clustering weighting variable was the subject of considerable research in cluster analysis [27]. Huang et al. [20] proposed the WK-means algorithm that can automatically calculate variable weights in the k-means clustering process. WK-means k-means algorithm standard with an additional step is extended to calculate the variable weights in each iteration of the clustering process. The variable weight is inversely proportional to the sum of the deviations of the variable within the cluster. As such, the noise variables can be identified and their effects on the compilation are significantly reduced. The proposed herein weight of two points of view and individual variables and is an extension of WK-means new algorithm. Domeniconi et al. [21] proposed algorithm adaptive local clustering (BAC), which assigns a weight to each variable group. They use an iterative algorithm for minimizing the objective function. Jing et al. [22] stated that "the purpose of the ALC is not differentiable maximum function. The convergence of the algorithm is demonstrated by substituting the largest average distance of each dimension at a constant fixed value." Jing et al. [22] proposed entropy weighting k-means (EWKM) also assigns a weight to each variable in each group. Unlike LAC EWKM extends the standard k-means algorithm with an additional step to calculate the variable weights for each group in each iteration of the clustering process. weight is inversely proportional to the sum of the deviations of variable in the cluster in the cluster. Hoff [23] proposed a multivariate Dirichlet process mixture model which is based on the model of a group Po lya urn "for multivariate means and variances. Model learned from a process Markov chain Monte Carlo. However, their computational cost is
prohibitive. Bouveyron et al. [24] proposed the GMM model that takes into account the specific sub-areas around which each group is, and therefore limits the number of parameters to be estimated. Chiu Tsai and [25] have developed a mechanism of self-weight adjustment variables for k-means in relational data sets, wherein the variable weights are calculated automatically, while minimizing separations within the clusters and maximize the intervals between the poles. Deng et al. [26] proposed a combination of mild improvement of the algorithm (ESSC) subspace, using both intra-cluster and between clusters information in the process of grouping subspace. Cheng et al. [27] proposed another Weighted very similar to the approach of BAC but allowing the integration of new constraints k-means. Traditional classification methods do not calculate variable weights weights for individual variables and does not take into account differences of views in data Multiview. Therefore, they are not suitable for clustering of multiview data.

3.2 Variable Waiting Multiview Clustering
Variables multiview grouping weighting as a combination of clustering and weighting method method of multi-view classification is a new direction for the pooling of multi-view data. To our knowledge, is the first SYNCLUS classification algorithm that uses weights for the two points of view and different variables in the clustering process. [28] Process for grouping SYNCLUS is divided into two steps. From an initial set of variable weight, SYNCLUS first uses the k-means clustering process to divide the data into k groups. We then calculate a new set of optimal weights optimizing a quadratic cost function with weighted average stress. The two steps iterate until the consolidation process converges to an optimal set of variable weights. SYNCLUS automatically calculates varying weights and light weights are given by users. Another weakness is that it is long SYNCLUS [29] so that we cannot handle large data sets. Tzortzis and Likas [9] proposed a weighted combination of model mixtures of copies for clustering multi-view data that assigns different weights to the views and learn these weights automatically. In each view, the data is modeled using copies of mixtures based models, called convex mixture models (MMC). [30]

3.3 Kracher K-means
Expectancy estimate (average) of a distribution is undoubtedly the most important step of all fundamental and statistical analysis. Given a sequence of X1, X2, ... Xk iid samples of a probability measure dP of R in one way estimator mk dP m is given by

\[ m_k = \frac{x_1 + x_2 + \cdots + x_k}{k} \]

The validity of the estimator of the course is guaranteed by the (weak) law of large numbers, which states that the estimator mk converges to the true mean m of probability. This well-known result is perhaps Fi first taught a class probability at the college level and professionals in statistics, machine learning and AI, which relies so deeply that we use many times without our immediate consciousness celui- thereof. The problem of interest in this thesis focuses on the random variables with values in a space that does not have a (vector space) the additive structure and in particular, the general distributions defined in (Riemann) manifold. This lack of additive structure is an important result because it means the formula 1 in the equation to calculate the estimate is no longer valid and, in fact, it is difficult to know how the media should be defined at all. More precisely, let (Ω, ω) is a probability space with probability measure of ω. A random variable real value X (more generally valued random variable vector) is a measurable set in Ω taking values in R (Rn, n> 1) function:
1. The distribution of the random variable $X$ is the push forward probability measure $dP_X = X^*\omega$ on $\mathbb{R}$, and its expectation $EX$ is defined by the integral

$$EX = \int_{\Omega} X \, dw = \int_{\mathbb{R}} x \, p(x) \, dx$$

A major reason for the above integral may be defined that $X$ takes on a value in a vector space, a space that allows additions of two points. However, if the purpose of the random variable $X$ has a structure of additive spring, the waiting definition through the above integral is no longer viable, and in particular the absence of additive structure must be replaced a guide structure useful space to properly determine and correct the wait.

3.4 Symmetric Positive-Definite (SPD) Matrix

(SPDP symmetric positive definite matrices are commonly found in many areas of science and engineering. For example, as the covariance descriptors in computer vision, tensor diffusion tensor imaging, Cauchy-Green in mechanics, metric tensor in many areas of science and technology. Find the average of a population dies as a representative of the population is also a frequently discussed problem in many areas. In recent years there has been a surge of activity in seeking ways for a population of such matrices, due to the abundance of data in the table of values in various fields, such as images of tensor diffusion [1] and elastography [16] in the medical image analysis, covariance descriptors in computer vision [14, 4] and learning dictionary Riemannian varieties [17, 7, 22] in learning the machine, etc.

It is well known that the space of $n \times n$ matrices equipped SPD GL $n$ is an invariant metric symmetric Riemann space [8] with negative sectional curvature [19], hereinafter referred to as $P_n$. Find the average of the data in $P_n$ can be achieved through a minimization process. More formally, the average of a set of data $x_i \in N P_n$ is defined by

$$X = \text{argmin}_x \sum_{i=1}^{n} d^2(x, x_i)$$

Where $d$ is the distance / divergence selected. Depending on the choice of $d$, we obtain different types of media. Many techniques have been published in the matrix calculation on the basis of half SPD different types of similarity / distance differences. In [20], symmetrized Kullback-Liebler was used to measure the similarities between the SPD matrices, and the average was calculated in closed form and is applied to image texture and diffusion tensor (DTI) segmentation. Karcher mean was obtained by using the GL-invariant (GL indicates the generally linear, that is to say the group of $n, n$) matrix invertible Riemannian metric on $P_n$ and used for segmentation in DTI [11] and interpolation [13].

4. Problem Statement

In the two-level variable weighting method, the variable weights $V$ are used to identify the important variables in each view, and the view weights $W$ are used to identify compact cluster structures within these views. If the view contains compact cluster structures, a large view weight is assigned so as to enhance the effect of such view; on the contrary, if the view contains loose cluster structures, a small view weight is assigned to eliminate the effect of such view. Compared with the traditional variable weighting method, the new method can take both individual variables and multiple views into consideration and capture the differences among different views and
variables. Moreover, the traditional variable weighting methods suffer from unbalanced phenomenon: the view with more variables will play more important role than the view with less variables. In the two-level variable weighting method, the view weights will be only determined in the view level, while the variable weights will be only determined in a view. Therefore, the two levels of variable weights will eliminate the unbalanced phenomenon and compute more objective weights. TW k-means can be considered as the two-level variable weighting clustering algorithm, but it only computes automated two-level variable weighting clustering algorithm but do not apply any Fuzzy and time saving approach. Proposed methodology apply time saving Karcher-SPD matrix approach and try to make clustering more realistic by applying Fuzzy k-means.

5. Proposed Methodology

It is used three tire K-means clustering approach where first two step namely initialization and weight assignment encapsulated in first tier which use TW-k-means for assign weight to each cluster element. Third and fourth ie Kracher K-Means and SPD matrix evaluation fall in second tire of proposed artier as show in figure 5.1 whereas fuzzy k-means comes in final step

![Figure 5.1: Proposed Methodology](image)

5.1 Weight assignment

The clustering process to partition X into k clusters with weights for both views and individual variables is modeled as minimization of the following objective function:

\[
P(U,Z,V,W) = \sum_{l=1}^{k} \sum_{i=1}^{n} \sum_{j \in C_t} w_t v_j d(x_{i,j}, z_{i,j}) + n \sum_{i=1}^{m} v_j \log(v_j) + \lambda \sum_{t=1}^{T} w_t \log(w_t)
\]

Where

- \( U = [PM]_{n \times k} \) = Partition matrix
- \( Z = \{Z_i\mid Z \text{ is centre of cluster} \} \)
- \( W = \{W_t\mid W \text{ is weight} \} \)
- \( V = \{v_i\mid \text{weight of } i^{th} \text{ variable} \} \)
The first term in (1) is the sum of the within cluster dispersions, the second and the third terms are two negative weight entropies. Two positive parameters $\lambda$ and $\eta$ control the strengths of the incentive for clustering on more views and variables.

5.2 Kracher and SPD matrix

A manifold-valued (M-valued) random variable $X$ is a random variable that takes values in a manifold $M$. Here manifold $M$ is assumed to be Riemannian, then it is possible to compensate for the lack of additive structure with its intrinsic geometric structure. Let $d_M(x, y)$ denote the Riemannian distance between two points $x, y \in M$. The integral in Equation 3 can be generalized to manifold-valued random variable $X$ by defining its Karcher expectation as equation 4.

$$m_k = \frac{x_1 + x_2 + \ldots + x_k}{k}$$ \hspace{1cm} \text{2}

$$EX = \int_{\Omega} X \, dw = \int_{\mathcal{R}} x \, p(x) \, dx$$ \hspace{1cm} \text{3}

$$KEX = \min_{\mu \in \mathbb{M}} \int_{\Omega} d_M^2(u^*, X) \, dw$$ \hspace{1cm} \text{4}

A direct approach would be to interpret $m_n$ in Equation 2 as the finite mean and accordingly define the $n$th Karcher estimator $m_n$ as

$$m_k = \min_{\mu \in \mathbb{M}} \sum_{i=1}^{k} d^2(u^*, X_i)$$ \hspace{1cm} \text{5}

However, this approach is undesirable because the computation of $m_k$ requires an optimization, and for large number of samples, it is usually unappetizing. Instead, we will generalize a slightly different but entirely equivalent form of Equation 2,

$$m_k = \frac{(k-1)m_k + x_k}{k}$$ \hspace{1cm} \text{6}

The mean of a set of $N$ data $x_i \in \mathbb{P}$ is defined by

$$X * = \arg\min_{X} \sum_{i=1}^{n} d^2(x_i, x)$$ \hspace{1cm} \text{7}

Where $d$ is the chosen distance/divergence. Depending on the choice of $d$, different types of means are obtained.

6. Implementation

The implementation of the proposed work has done in MATLAB 10.0 with the help of MySQL database. This work uses Intel core i3 CPU with 2.53 GHz, having 4 GB of RAM and 500 GB HDD. We worked on 32 bit OS (Windows 7).

6.1 Matlab

MATLAB is a high-level technical computing language and interactive environment for algorithm development, data visualization, data analysis, and numeric computation. MATLAB is a software program that allows you to do data manipulation and visualization, calculations, math and programming. It can be used to do very simple as well as very sophisticated tasks. Image Processing Toolbox provides a comprehensive set of reference-standard algorithms and graphical tools for image processing, analysis, visualization, and algorithm development. You can perform image enhancement, feature detection, noise reduction, image segmentation, spatial transformations. Mathematically, we used sum, sine, cosine, and complex arithmetic, matrix inverse, matrix Eigen values, Bessel functions, and fast Fourier transforms. We wrote programs in C/C++ and FORTRAN languages that interact with MATLAB.
6.2 Workspace Browser

In order to view the workspace or to get information regarding variables used in the work, there is a need to use the Workspace browser, or also can use the functions who. In order to delete any variable from the workspace, we can take action by selecting the specific variable and then on Edit option apply Delete action. The clear function is use to clear the screen. Is not retained after completion of the session of MATLAB workspace. To save the workspace into a file that can be read by a later MATLAB session, select the option to save the files and the application of the work, or use the save function. This provides a workspace in a binary file called MAT, which contains the extension .mat file. You can use options to save in different formats. To read on the MAT file option to submit identify and implement procedures to import the data, or using function condition.

![Workspace Browser](image)

Figure 6.2.1: Workspace Browser
Indushekhar Mishra: Fuzzy TW-k-Means: A Weighted Fuzzy Approach for Clustering Two-Level Multiview Data

Figure 3: Initialization Screen

This Screen shows the initialization parameter of the proposed work which required at the time of execution. Here the total samples are 1000 and dominations and clusters are 3.

Figure 4: First Output screen.
This screen shows the number of iterations and time required during the execution. This is a first output. The iteration takes place number of time.

7. Result Analysis And Graphs

- **Distance Computation Time:** In the process of clustering over multi view data set need to compute distance between different items over data set. Main approach of researcher to minimize the time required to compute distance between different item set that’s lead overall system faster and efficient.

<table>
<thead>
<tr>
<th>Number</th>
<th>TW K-means</th>
<th>Fuzzy TW-K-means</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.19</td>
<td>0.17</td>
</tr>
<tr>
<td>2</td>
<td>2.15</td>
<td>1.8</td>
</tr>
<tr>
<td>3</td>
<td>0.73</td>
<td>0.71</td>
</tr>
<tr>
<td>4</td>
<td>3.72</td>
<td>3.7</td>
</tr>
<tr>
<td>5</td>
<td>3.72</td>
<td>3.5</td>
</tr>
<tr>
<td>6</td>
<td><strong>3.89</strong></td>
<td><strong>3.76</strong></td>
</tr>
<tr>
<td>7</td>
<td>4.17</td>
<td>3.8</td>
</tr>
<tr>
<td>8</td>
<td>10.87</td>
<td>10.56</td>
</tr>
<tr>
<td>9</td>
<td><strong>10.67</strong></td>
<td><strong>10.59</strong></td>
</tr>
</tbody>
</table>

TW K-Means required slightly more time than proposed fuzzy TW K-means as show in table 1 and represent in figure 7.1. The bellow graph is a comparison of Distance Computation Time (in Second).

Figure 7.1: Graph for Distance Computation Time
• **Mean Computation Time**: For any clustering approach recently researcher focus towards fast and efficient clustering approach. Towards this aim Mean computation time need to minimize for one of better clustering approach.

<table>
<thead>
<tr>
<th>Iteration</th>
<th>TW K-means</th>
<th>Fuzzy Tw K-Means</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.15</td>
<td>0.09</td>
</tr>
<tr>
<td>2</td>
<td>0.17</td>
<td>0.09</td>
</tr>
<tr>
<td>3</td>
<td>0.18</td>
<td>0.1</td>
</tr>
<tr>
<td>4</td>
<td>0.31</td>
<td>0.23</td>
</tr>
<tr>
<td>5</td>
<td>0.33</td>
<td>0.2</td>
</tr>
<tr>
<td>6</td>
<td><strong>0.42</strong></td>
<td><strong>0.34</strong></td>
</tr>
<tr>
<td>7</td>
<td>1.23</td>
<td>1.12</td>
</tr>
<tr>
<td>8</td>
<td>1.89</td>
<td>1.56</td>
</tr>
<tr>
<td>9</td>
<td><strong>2.34</strong></td>
<td><strong>2.1</strong></td>
</tr>
</tbody>
</table>

TW K-Means required slightly more time than proposed fuzzy TW K-means as show in table 7.2 and represent in figure 7.2

**Figure 7.2**: Graph for Mean Computation Time

8. **Conclusion**

In this dissertation, a novel recursive three tier K-means algorithm has been proposed which use TW-k-means with two-level variable weighting clustering algorithm for clustering of multi view data is presented which encapsulate Karcher expectation estimator for symmetric positive definite (SPD) matrix-variant random variables and at last apply fuzzy approach r, fuzzy K-means provides the flexibility to employ different fuzzy membership function to measure the distance between multi view data.
Here it seems to be that can TW k-means calculates weights for the views of individual variables at a time in the assembly process. With these two types of weights, compact views and important variables can be identified and can reduce the views of the poor quality and the effect of noise variables. Karcher expectation estimator is used for computing the cluster centers in a K-means clustering algorithm applied to SPD manifold-valued data, and experimental results clearly demonstrate the significant improvement in computational efficiency over the non-recursive counterpart.

9. Acknowledgement

Whenever we are standing on most difficult step of the dream of our life, we often remember the great almighty god for his blessings kind help. And he always helps us in tracking on the problems by some means in our lifetime. I would also like to extend my gratitude to our respected Prof. Pankaj Kawadkar, HOD in the Department of Computer Science & Engineering, at Patel Institute of Engineering & Science, Bhopal for their kind co-operation for the betterment and successful completion of this paper and support they ever provided to me. And last but not least I would also like to thanks my parents and all my friends for their encouragement from time to time. Finally, I am very grateful to Mighty God and inspiring parents who loving and caring support contributes a major share in completion of my task.

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