ISSN 2229-5518

Object Evidence Instance Feature Mapping Using Support Vector Machine

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Abstract—This is the matter of fact that Multiple Instance Learning (MIL) has established itself as a potential technique for Multimedia Data Mining applications and various other classification and prediction problem. As per our till date knowledge most of the researches have employed conventional MIL schemes for mining and classification. Still, majority of researchers could not address the key issue of ambiguity in the prime hypothesis of MIL that a bag having at least one Positive Instance would be a labelled as Positive Bag, where the classification has to be done. But this hypothesis raises the question of ambiguity, because a positive bag having single positive instance might be remaining as negative, and hence the classification and prediction would be either computationally very complex and would be suffering from classification accuracy issues. In this research work a highly robust Object Evidence Instance Feature Mapping Using Support Vector Machine scheme has been proposed that intends to provide much efficient classification and prediction for multimedia data mining applications.

Index Terms—Multimedia, Data Mining, support vector machine, Classification, Prediction, Multiple Instance Learning, Feature Mapping.

1 Introduction

DEFINING multimedia data mining, it can be stated as an interdisciplinary research field in which generic data mining theory and techniques are employed to the multimedia data sets to facilitate multimedia-specific information or knowledge discovery purposes. In fact, it is a combination of multiple media data like text, image, video, audio, numeric, sound files, animation, and graphical and categorical data categories. Multimedia data mining has become one of the most popular research domains these days that assists extraction of the expected and significant information from the multimedia data sets.

In general, the multimedia data is classified into two categories:

1. Static media such as text, graphics, and images and
2. Dynamic media such as animation, music, audio, speech, and video.

The process of multimedia data mining states for the analysis of huge multimedia information to explore patterns or statistical relationships. In general, the multimedia data becomes highly intricate as the sequence progresses and ultimately the concept being mined might even vary. Thus, representing and understanding the significant variations in the mining process is an inevitable need for mining certain multimedia data. The two predominant multimedia data types, unstructured and semi-structured are stored in multimedia databases where the multimedia mining is implemented to explore certain significant information from large multimedia database system by means of numerous multimedia techniques. In general, multimedia database system comprises a robust multimedia database management system that processes and facilitates as the foundation for data retrieval, storage, manipulation and various objective oriented applications. As already stated, the data are increasingly available in both the unstructured as well as semi-structured types and hence poses huge intricacies in extracting the hidden information manually, significant information embedded within the multimedia collections without the implementation of certain new techniques and powerful tools. These intricacies drive the requirement to develop certain advanced and robust mining tools and techniques that might be efficiently employed for the mining significant information from multimedia data.

2 Procedure for Paper Submission

1.2Multimedia Data mining

Advances in multimedia data acquisition and storage technology have led to the growth of very large multimedia databases. Analysing this huge amount of multimedia data to discover useful knowledge is a challenging problem. This challenge has opened the opportunity for research in Multimedia Data Mining (MDM). Multimedia data mining can be defined as the process of finding interesting patterns from media data such as audio, video, image and text that are not ordinarily accessible by basic queries and associated results. The motivation for doing MDM is to use the discovered patterns to improve decision making. MDM has therefore attracted significant research efforts in developing methods and tools to organize, manage, search and perform domain specific tasks for data from domains such as surveillance, meetings, broadcast news, sports, archives, movies, medical data, as well as personal and online media collections.

1.3 Final Stage

In the following figure an illustrative figure of multimedia data mining is provided. In general, the multimedia data mining comprises multiple components. Some of the significant components of multimedia data mining are given as follows:

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1. Data Input
2. Multimedia Content
3. Feature Extraction
4. Finding the similar Patterns and
5. Evaluation of Results.

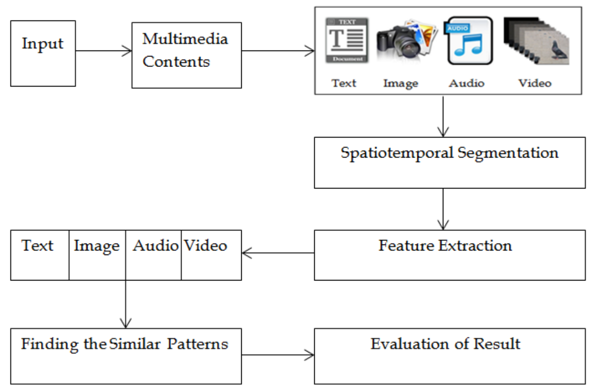

Fig. 1. Multimedia Data mining Architecture.

1. Input: This is the phase where the multimedia database is employed to explore certain patterns for exhibiting data mining process.
2. Multimedia Content: It refers the data selection phase in the multimedia data mining that needs user to specify the data to be explored and analysed. In this proposed research the benchmark data for mining images where huge unannotated data are available has been used for classification using proposed MIL based multimedia data mining.
3. Feature extraction refers the process of pre-processing step that comprises integrating data elements from varied sources in varied form and then making choices concerning characterizing certain data fields so as to serve for pattern finding stage. In multimedia data mining, the pre-processing stage is of great significance, as the data might be in unstructured manner.
4. Finding the similar pattern This phase is considered as the heart of the overall multimedia data mining process. The hidden patterns and trends in the data are in general explored in this stage only. Few of the approaches for exploring similar pattern stage comprise association, classification, clustering, regression, time-series analysis and visualization.
5. Results evaluation is the stage of data mining which is employed for evaluating the processed results and is highly significant so as to determine whether the previous stage should be iterated or reprocessed or not. In fact, this phase comprises reporting and making use of the extracted information to generate certain new actions or products and services or marketing strategies.

2 Literature Survey

MIL approach has been employed for multimedia data mining and information retrieval. Some of the predominant researches conducted for MIL problems are discussed in the following section.

Tang et al [1] worked on progressive association rules mining algorithm based on image content, where they used the characteristic of two images in a resolution level to explore various associations for content based information retrieval. A work was done by Sheikh et al [2] who developed a gradient vector flow based CBIR system and evaluated varied segmentation techniques for multimedia data classification system. Using road data segmentation and analytical approach, researchers Dechen et al [3] proposed a traffic surveillance system and status monitoring system and an approach for image acquisition and feature selection was done by Chen et al [4]. Using image benchmark researchers exhibited their proposed research achieves better training images for learning where the classification error is reduced by 23.35% as compared to the text-based approach.

Zhouyu et al [5] addressed the key issue of instance selection in MIL and proposed an instance selection measure which is based on an alternative optimisation framework by repeating instance selection and updating classifier learning. Unfortunately, such system may be highly computational complex and time consuming, which confines the applicability of such systems in real world. To work on instance selection for MIL, Zhang et al [6] used constructive covering algorithm (MilCa) by means of maximal Hausdorff scheme for selecting some initial positive instances from positive bags, which was followed by a Constructive Covering Algorithm (CCA) to restructure the structure of the original instances of negative bags. Further, they employed inverse testing to rule out the false positive instances from positive bags. Such system might be highly intricate and less effective for real time applications. Dundar et al [7] studied learning of a convex hull representation of multiple instances for CAD utilities. Yao et al [8] presented a semantic image retrieval approach on the basis of MIL. They employed MIL that realizes the mapping from low-level features to simple semantics and the mapping from simple semantics to compound semantics by means of multiple-instance learning. Bolton et al [9] developed MIL for learning a target concept in the presence of noise or with an uncertainty in target information including class labels. In later research, [10] researchers developed methods to incorporate spatial information into the MIL framework while maintaining the benefits of the Spatial Multiple Instance Learning (S-MIL) method for the purposes of landmine detection.

3 Converting Image into a MIL Bag and Instances

In this section, the approach of initial bang generation and respective instance selection scheme has been discussed which has been followed by optimization through the proposed object evidence verification scheme for multimedia data mining applications.

In the implemented MI-Winnowing scheme encompasses the image representation of Accio [11] in which all images are first transformed into the YCrCbcolour space which is then followed by pre-processing by means of a wavelet texture filter so that each pixel in the image could have three color features and three texture features. In the data preparation, a segmentation algorithm has been employed that segments the image into 32 distinct segments. As, the specific context in which a segmentation takes place may be of great significance for defining what the user wants, it is augmented the feature information for the individual segment with the difference between its neighbours' value and its value for each of the six features for its neighbour to the right, bottom, left, and top.

In summary, let I be the segmented image. In the neighbour bag generator, each segment $x \in I$ is a point in a 30-dimensional feature space where the first 6 features hold the average color and texture values for x, the next 6 features hold the difference between the average color and texture values of x and the northern neighbour. Similarly there are 6 features for the difference information between x and its other 3 cardinal neighbours. So each image is represented as a bag of 32 such points. In the no-neighbour bag generator, each segment $x \in I$ is a point in a 6-dimensional feature space with just the color and texture values for the segment itself. Even though this feature space is a subset of the feature space of neighbour bag generator some results are better for this generator.

In fact, in our proposed model, we have considered the processed image benchmark data for mining and classification accuracy, so we need not to process data as discussed above.

3.1 Winnowing

An influential result in the online model is Littlestone's noise-tolerant algorithm Winnow [12] for learning disjunctions among a set of N attributes in which only k (for $N \gg K$) of the attributes are relevant. In general, Winnow makes predictions based on a linear threshold function, given as follows:

$$\hat{y}_t = \begin{cases} 1 & if \sum_{i=1}^{N} w_i x_i \geq \theta \\ 0 & otherwise \end{cases} \tag{1}$$

where w_i is the weight associated with the Boolean attribute x_i and θ is generally set to $N/2$ (unless additional prior information is known about the target concept). If the prediction is wrong then the weights are updated on a false negative prediction, for each attribute x_i, where $x_i = 1$, Winnow updates the weight w_i by multiplying w_i by some constant update factor, stated as $\alpha > 1$. On a false positive prediction, for each attribute x_i where $x_i = 1$, Winnow decrements the weight w_i by dividing it by the constant update factor α.

In fact, Winnow can be stated to be the similar approach as the classical Perceptron algorithm [13], except that the Perception algorithm updates its weights *additively* while Winnow uses multiplicative weight updates. Furthermore, major difference between these algorithms is that when learning disjunctions over n attributes with k of them relevant, Winnow's mistake bound is logarithmic in N whereas the Perceptron algorithm's mistake bound can be linear in N in the worst case [14]. Thus Winnow is a good choice when there are many irrelevant features. Such situations are prevalent in multimedia data with lower annotation provisioning. Here, we learn a box in the MIL model using the same basic approach of Maass and Warmuth[15] to learn a box in a discrete d-dimensional space $\{0.1 \ldots .\ n-1\}^d$. For each of d dimensions they introduce $2n$ halfspaces – n directed in each direction for each discrete value. Thus, the implementation of Winnow technique can be used significantly to determine which of the 2d half spaces from among the 2dn possible half spaces are relevant. Thus, in this research or thesis work, we have employed the Multiple Instance-Winnowing (MI-Winnow) scheme for initial instance generation and bag labelling. The following section discusses the MI-Winnowing process, employed in the proposed multimedia data mining and classification purposes.

3.2 Multiple-Instance Winnow

This section of the presented manuscript, mainly discusses the multiple-instance winnowing (MI-Winnowing) approach implemented for initial instance generation and bag labelling. A predominant contribution of the proposed MI-Winnow is its handling capability towards the ambiguity inherent in not knowing which point in a positive bag is responsible for the positive label. In this research model, initially the conventional diverse density scheme has been employed which has further been enhanced using the proposed evidence verification model. The implemented MI-Winnowing scheme employs diverse density (DD) measure, over the points in all positive bags, to select a set of candidates for truly positive points called evidence or object region of interest. It is then followed by the creation of the negative training data from all the points in negative bags, and the Winnowing is trained so as to generate a box. Then the hypotheses obtained from multiple runs of Winnowing (possibly with data obtained using different bag generators) are combined to create a final hypothesis.

Now, here we intend to present how a bag can be converted to a standard example (with one point) for Winnowing in the proposed mining scheme and object classification. Recall that a bag is positive if at least one point in the bag is positive. However, the learning algorithm can only see the label for the bag. In the proposed research work, we have defined a *true positive* point to be a point from a positive bag that has the same label as the bag. What makes MIL hard is that a positive bag might only contain one true positive point – the other points in the bag could be false positives. In contrast, all points in a negative bag are truly negative. For the moment, suppose MI-Winnowing could locate a truly positive point p from a positive bag. Then for any other positive bag, the closest point in that bag to p is very likely to also be a positive point. That is, the set B^+ of the closest point to p from all other positive bags should contain mostly positive instances if p is truly positive. Let B^- contain all points from the negative bags. If p is truly positive then B^+ and B^- will be consistent with a d-dimensional box which can be learned with winnowing process.

A number of existing approaches or algorithms address the difficulty of finding a truly positive point by trying each point from a set of positive bags as the candidate for p. However, such an approach is computationally expensive. Multiple Instance winnowing proposes the alternate approach of using the training data to filter the points from the positive bags to determine which ones are most likely to be truly positive since those are the points that will produce the best results. In order to accomplish these objectives, in the proposed model, the diverse density (DD) estimation has been done [16].

In our proposed model for the preliminary instance generation and bag labelling, the following implementation paradigm has been employed. Let $dist(P_i, P_j)$ be the Euclidean distance between points certain points P_i and P_j and $d_h(p) = exp(-dist^2(h,p))$. Institutively, $d_h(p)$ can be taken into consideration as the probability that p is positive as per h. Implementing Gaussian centered on h so as to convert the distance to this probability measure, treated as a real valued label for p. Consider, the density of hypothesis h be $DD(h) = \prod_{i=1}^{n} \max_j \left\{1 - \left|y_i - d_h(x_{i,j})\right|^2\right\}$. Putting a glance on the derived function, it can be found that the term $\left|y_i - d_h(x_{i,j})\right|^2$ is the absolute loss between the true label y_i for bag x_i and the label that would be given to the jth point $x_{i,j}$ in x_i. Thus, the term inside the maximum of the $DD(h)$ definition refers the measure of the probability that label y_i being given to bag x_i is correct based on point $x_{i,j}$. The label for each bag represents the probability for the best point in the bag. Ultimately, under the assumption of independence between the points in a bag, of a uniform prior of the hypothesis space, $DD(h)$ refers the probability of h being the object based on the labeled data L.

The employed preliminary instance generation and bag labelling scheme, Multiple Instance Winnowing estimates the diversity density (DD) of all points in the individual positive bag to determine which points are most probable to be truly positive. The developed algorithm considers only these points as a candidate for a truly positive point p. This method generates fewer candidate points for Winnow, and the resulting hypotheses are more likely to be accurate. An overview of MI-Winnow is shown in Figure 3.1. We partition the training bags B into $\{(B_1^+, B_1^-), \ldots, (B_b^+, B_b^-)\}$, where each pair is generated by a different bag generator. While all points created by the same bag generator must have the same dimensionality, different bag generators need not generate points of the same dimensionality. The implemented winnowing scheme takes two parameters, τ which control how many different candidates are considered as the truly positive point, and s which controls the number of variables used by Winnow.

This is the matter of fact that the employed Multiple Instance Winnowing approach has generated multiple instances and respective tentative bag labelling has been done appreciably, still this approach could not discuss the prime ambiguity of the multiple instance learning, and hence the key requirement of a successful multimedia data mining was missed. It was the confirmation where the object evidence of the true object instance is classified accurately or not. In order to eliminate such issues and limitations, in this research work or the proposed model, the evidence verification has been done that ensures optimal mining and classification of huge unannotated datasets. Here we have considered two large scale multiple instance learning benchmark datasets, SIVAL and COREL that comprises images of 1500 and 2000 respectively. These all images are of different categories and possessing diverse features such as background, colour, orientation, view points etc. The intended research model intends to perform mining over these data elements and classify them correctly. The novelty of the proposed research work can be understood in the term that it ensures optimal and accurate instance selection and its verification across bags generated. It enables mining scheme to deliver optimal classification of huge unannotated data.

The discussion of the proposed object evidence verification model is given in the following section.

3.3 Object Evidence Instance Feature Mapping

In this proposed research work, once the evidence instance verification has been done, the identified instances have been processed for feature mapping where the individual Bag $\mathcal{B}_i$ has been mapped to a point $\varphi(\mathcal{B}_i)$ in the object evidence instance on the basisof its feature vector, which is given as follows:

$$\varphi(\mathcal{B}_i) = \left(p(Ins_{ev_1}.\mathcal{B}_i).(Ins_{ev_2}.\mathcal{B}_i).\ldots.(Ins_{ev_{|Ins_{EV}|}}.\mathcal{B}_i)\right)^T \quad (2)$$

Where, $Ins_{ev_i} \in Ins_{EV}$, Ins_{EV} is the set of identified or verified object evidence instances and the distance parameter $p(Ins_{ev_i}, \mathcal{B}_i)$ is evaluated using following equation:

$$p(Ins_{ev_i}, \mathcal{B}_i) = \min_{\mathcal{B}_{i,j} \in \mathcal{B}_i}\left(\left\|Ins_{ev_i} - \mathcal{B}_{i,j}\right\|^2\right) \quad (3)$$

In fact, it states that the distance between an object evidence instance and a bag should be same as that of the distance between n instance and the closest instance in the bag. In this proposed research model, the process of feature mapping is of great significance as in general it is found that the distance between two object evidence instances in a bag would always be smaller than the distance between an object evidence instance and a non- object instance in the image of bag under process. Since, the bags labelled as positive comprises object evidence instances, and hence the distance between an evidence instance and a positively labelled bag should always be less than the distance between an evidence instance and certain negative bag.

Performing object evidence instance verification, in this research model, a robust feature mapping scheme has been implemented that performs mapping of instance features to form bags labelling and thus the training data comprising positive as well as negative instances $E = \{\mathcal{B}_1^+, \mathcal{B}_2^+, \ldots, \mathcal{B}_{m^+}^+, \mathcal{B}_1^-, \mathcal{B}_2^-, \ldots, \mathcal{B}_{m^-}^-\}$ have been prepared. In the proposed research model, the labelling of the images or the bags has been done using evidence instance verification outcome and thus similar to the previous research phase, the MIL problem has been converted into equivalent single instance learning where SVM has been used for multimedia data classification with varied benchmark datasets.

In the implementation, for individual bag, there is the labelling of $y_i \in \{+1, -1\}$ where the comprising instances possess its feature vectors of similar dimensions. In our proposed model, it can be found that the evidence instance verification is required to be done only for the observed instances in the labelled bags and hence these can be estimated directly from the training data. Thus, in this aspect also the proposed system in this thesis is better than other existing systems.

4 Support Vector Machines

Classification is performed by a support vector machine (SVM). In this proposed research work, Support vector machines (SVM), which has established itself as a potential tech-

ISSN 2229-5518

nique for classification, mining and machine learning, has been used for feature classification on the mapped data. Here, we have implemented linear SVM mechanism that classifies the data and intends to form hyperplace while ensuring maximum margin between two distinct classes (SVM http://www.csie.ntu.edu.tw/~cjlin/libsvm). It transforms the linear mapped data into higher dimensional feature space.

In this research work, the implementation of linear SVM has been illustrated as follows:

The objective of SVM is to maximize the instance margin jointly over unlabeled instances. Following is a kernelized discriminate function:

$$\min_{\{y_i\}} \min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum \xi_i \qquad \text{Eq. (4)}$$

where W is normal vector to hyperplane, b is the bias , C is a regularization parameter and ξ is slack variable. In the proposed SVM classifier, the second part of the constraint imposes a relationship between

$$subject\,to\,\forall_i: y_i(\langle w, x_i\rangle + b) \geq 1 - \xi_i\ , \xi_i \geq 0, y_i \in \{-1, 1\} \qquad \text{Eq. (5)}$$

bag labels and instance labels. In comparison, the objective of MI-SVM is to maximize the bag margin. This kernelized discriminate function:

$$\min_{w,b,\xi} \frac{1}{2}\|w\|^2 + C\sum \xi_i$$

$$subject\ to\ \forall_I: y_I \max_{i\in I}(\langle w, x_i\rangle + b) \geq 1 - \xi_i\ , \xi_i \geq 0 \qquad \text{Eq. (6)}$$

Note that, the margin of each instance is considered in mi-SVM and to maximize the margin it is possible to set the instance label variables subject to constraints of their bag labels. In comparison, in SVM only one instance from each bag is considered to define the margin of the bag.

The implemented approach for object classification in the proposed research model is given as follows:

Consider, a training set $\mathcal{T}_{Set}$ comprising elements or feature vectors

$$\mathcal{T}_{Set} = \{(\mathcal{X}_1, y_1), (\mathcal{X}_2, y_2), \ldots, (\mathcal{X}_{|\mathcal{T}_{Set}|}, y_{|\mathcal{T}_{Set}|})\} \qquad \text{Eq. (7)}$$

Where $\mathcal{X}_i \in F_{Space}{}^m$, $y_i \in \{+1, -1\}$ and $|\mathcal{T}_{Set}|$ be the total number of instances in the training set $\mathcal{T}_{Set}$.

In SVM, a nonlinear mapping function $\varphi(.)$ is employed to perform mapping of the dataset from the input feature space $\mathcal{X}_i \in F_{Space}{}^m$ into higher dimensional feature space, and thus all the comprising classes are supposed to be linearly separable. In general, the prime objective of SVM implementation is to retrieve the two predominant variables w and bias parameter b, which form the optimal hyperplace for data classification. Mathematically it can be presented as follows:

$$\mathcal{D}_{\mathcal{W},b}(\mathcal{X}) = \mathcal{W}^T\varphi(\mathcal{X}) + b = 0 \qquad \text{Eq. (8)}$$

For classification, the above equation, called decision function fulfils the following conditions:

$$y_i(\mathcal{W}^T\varphi(\mathcal{X}_i) + b) \geq 1 - \xi_i, \qquad i = 1, \ldots, |\mathcal{T}_{Set}|,$$
$$\xi_i \geq 0, \quad for\,i = 1, \ldots, |\mathcal{T}_{Set}| \qquad \text{Eq. (9)}$$

where ξ_i represents the Lagrangian Relaxation parameter that leverages or relaxes the margin factor to make classification efficient. In order to make SVM efficient for huge data sets and for efficient classification, the following mathematical problem is needed to be solved.

$$\min F(\mathcal{W}, b, \xi) = \frac{1}{2}\mathcal{W}^T\mathcal{W} + C\sum \xi_i \qquad \text{Eq. (10)}$$

where C represents the regularization parameter that leverages the hyperplane margin and errors during classification. Implementing Lagrange relaxation function, these key variables, w and b are solved, which is then followed by decision classifier (Equation-8). In this research model, to perform classification of $\mathcal{X}$ features or instances, an instance is classified as positive if and only if $\mathcal{D}_{\mathcal{W},b}(\mathcal{X}) > 0$, otherwise it classifies instance as negative.

The presented multimedia mining model intended towards evidence verification or the object evidence verification and hence thus these systems can be much efficient and applicable for the content based information retrieval system, where certain target is localized in huge images and the specific embedded content based classification has to be done. In recent technological trends of mobile applications, image processing, surveillance systems etc, such system can be of great significance.

5 Analysing and Accessing Data

MATLAB maintains the whole data analysis procedure from obtain data from outside devices in addition to databases, during preprocessing, apparition, and numerical investigation, to producing management excellence output

Eq. (6)

5.1 Data Analysis

MATLAB facilitates interactive tools along with commandline purpose for data study operations, comprising:

- Interpolating as well as decimate
- extort segment of data, scaling, as well as averaging
- Threshold as well as smooth
- connection, Fourier investigation, and filtering
- 1-D peak, valley, as well as zero finding
- essential statistics and curve fitting

Eq. (7)

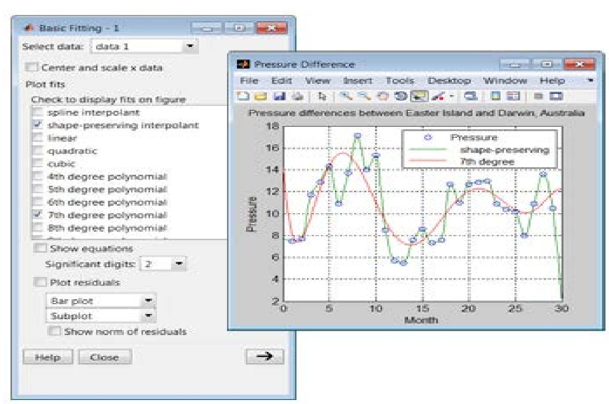

Fig. 2. Plot show curve fitted to the review averaged atmospheric demands differences involving Easter Island as well as Darwin, Australia.

5.2 Data Access

MATLAB is a well-organized proposal for entrance data from files, additional applications, databases, along with outer devices. We can examine data from admired file formats, such as Microsoft Excel, $ASCII$ text or binary files, picture, sound, and video files as well as scientific files, like as HDF and $HDF5$.

ISSN 2229-5518

Low stage binary file Input/output functions allow you effort with data files in some format. Further functions let single examine data from Web pages as well as XML.

Individual call other applications and languages, like$C$, $C++$, COM object,$DLLs$, Java, FORTRAN, as well as Microsoft Excel, and contact FTP sites in addition to Web services. Using Database Toolbox, individual can also access data from $ODBC/JDBC$compliant databases. Particular preserve obtain data from hardware devices, such as the computer's sequential port or noise card. Using Data possession Toolbox, one can stream survive, measured data honestly into MATLAB for analysis as well as visualization. Instrument Control Toolbox makes possible communication with $GPIB$ and VXI hardware.

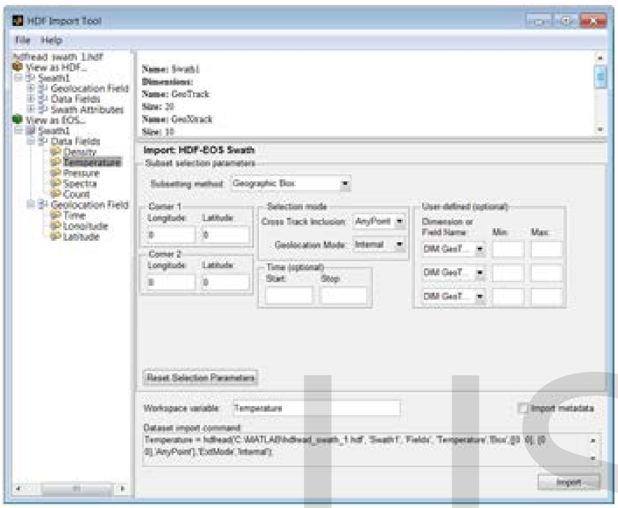

Fig. 3. HDF data from a satellite selected as well as significance into MATLAB by the MATLAB HDF Import Tool.

6 Conclusion and Future Work

The high pace increase in internet contents and specially multimedia contents such as image data has demanded certain optimal mining scheme to classify data as per under needs. On contrary, the annotation of all the image data is not feasible and hence classification based on conventional semantic approaches is not universal. Some of the conventional approaches such as traditional single instance learning schemes like Artificial Neural Network, Support Vector machines, association rule mining etc require complete data description and feature presentation to perform classification. Specifically ANN demands complete annotation of the data under consideration, on contrary in the present day scenarios, majority of databases are unstructured and majority of data may be unannotated. Taking into consideration of such functional limitations of the existing mining approaches. Furthermore, considering limitations of the existing conventional MIL systems that seems to be ambiguous for optimal classification and instance selection, in this thesis a robust evidence verification model has been developed that ensures the presence of positive instances in the positive bags and enables classification as optimal.

The developed scheme has employed simple prior information to estimate how many evidence or object instances must be identified from individual positive bag, which has strengthened the system to better learn the parameter from image data. The implementation of the proposed mining model can be highly effective for applications such as content based multimedia information retrieval, biomedical image categorization and classification or computer added diagnosis, supervision system and security application. In summary, the developed mining model can be implemented for image repository of any huge size with major unannotated data or unlabelled data, which is common in present day applications. This system can be an optimal system for Localized Content Based Image Retrieval (L-CBIR) application. In future, the developed system can be strengthened by means of introducing dynamic instance selection per image (in our approach we have taken five instances per images), and evolutionary computing based classification system such as Genetic Algorithm (GA) based support vector machine can be used with optimal regularization parameters and scaling factor. In future, the system can be used for other type of multimedia data types and its mining as well as classification.

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