

Temporal Information Based Organizing of Multimedia Archives

Srikanth Lakumarapu¹, Dr. Rashmi Agarwal²

¹Research Scholar, ²Professor
Department of Computer Science & Engineering,
Madhav University, Bharja, Rajasthan, India.

Abstract

Every day of life, which merged with Computer erected information systems have stayed in use for numerous decades, several organizations have now built up computerized archives of their activities in the former. Those documents are often valuable, in that the former patterns of behavior can be used to predict imminent behavior. Historical databases also are known as Temporal databases. It provides support for the efficient storage and querying of such information. In real life, Media information has time attributes either implicitly or explicitly known as temporal data. A temporal database that has time as the mandatory field is considered to make the system more practical and realistic. The levels of data onto temporal database are optimized in time base by encoding the temporal database for the efficient memory utilization. The idea is to perform temporal data mining on multimedia files in order to classify according to their prominence from the user outlook. Timestamp for multimedia data like resolution, timestamp of creation and modification analyzed based on the variation during optimization and reviewed.

Keywords: Temporal, Multimedia, Data Mining, Metadata, TMFA, EXIF, IPTC-IIM, and XMP.

TEMPORAL INFORMATION BASED ORGANIZING OF MULTIMEDIA ARCHIVES

In recent years, with billions of devices involved in mobile Internet, data volume is undergoing an extremely rapid growth. Therefore, data processing and network overload have become two urgent problems. On the part of data processing, Data mining is one of the authoritative new technologies that has emerged and It smooths the users both individuals and organizations to dig and find data from assortment or a large cluster of data. Data mining is used to find patterns of a huge group of data. Data mining is the method of finding patterns, trends, and relations by moving over and done with a huge amount of data stored in data repositories. This is finished using techniques like statistics and mathematics. In data mining, data is analyzed over and done with different views in order to find the patterns that satisfy our needs. In short, data mining is also an analytical method. Data is stored in various forms like images, text, sound, videos etc. Using data mining we can categorize data, relate similar data, and find the data occurrence patterns. Data mining has two ways of dealing with data namely Classification and Prediction. Classification: Classifies data founded on the training set and the values of a classifying attribute and uses it in classifying new data. Prediction: Predicts unknown or missing values as stated in Sankar K.V, Uma.S, Subin.P.S, Ambat Vipin (2014).

Temporal data are sequences of a major data type, most typically numerical or categorical values and infrequently multivariate or combination information. Examples of temporal data are regular time series (Example is EEG, stock ticks), event sequences (Example medical records, sensor readings, weblog data, packet traces), and temporal databases (Example relations with databases with versioning, timestamped tuples). The temporal database normally includes two-time aspects namely, valid time and transaction time. Valid time represents the time period during which a fact is true with respect to the real world. Transaction time is the time period throughout which a fact is stored in the database. These two-time features allow the distinction of three altered forms of temporal databases. They are (i) A historical database stores data onto admiration to valid time. (ii) A rollback database stores data onto admiration to transaction time. (iii) A bitemporal database stores data onto admiration to both valid and transaction time, that is, they store the history of data onto admiration to valid time and transaction time. A temporal database maintains three majored datatypes: temporal data, static data, and snapshot data. Regardless of the data type, the temporal data mining algorithms should be translucent and should treat all data as some form of temporal data.

Temporal data mining tasks that works with temporal data types can be collected into (i) prediction (ii) classification (iii) clustering (iv) to search & retrieval and (v) pattern discovery is stated in Pughazendi.N, Punithavalli.M (2011). Temporal Mining analyses temporal data to get patterns or regularities. There are many techniques included in temporal data mining. Sequential association mining, cyclic association mining, stock trading rule mining, patent mining, clinical mining, image time series mining, software adoption and penetration mining, temporal utility mining, fuzzy temporal mining, and calendar association mining all belong to it. There are also a variety of applications for temporal data mining as suggested in Tzung-PeiHong, Guo-ChengLan, Ja-HwungSu, Pei-ShanWu, Shyue-LiangWang (2016).

Image mining denotes the synergy of data mining and image processing technology to aid in the analysis and considerate in an image-rich domain. In fact, it is an interdisciplinary endeavor that draws upon expertise in computer vision, image processing, image retrieval, data mining, machine learning, database, and artificial intelligence. The benefits of image classification and clustering to include better image storage and management, and optimized image-indexing schemes for fast and efficient image retrieval, all of which are also essential to the image mining systems. In view of the differences and correspondences with image classification and clustering, we

present the following generic steps essential in the image classification and clustering:

- (a) Pattern representation. This may include image processing such as image segmentation, feature extraction, and selection.
- (b) Definition of image proximity measures appropriate to the domain.
- (c) Classification or clustering.
- (d) Group abstraction or adaptation. (as cited in Ji Zhang, Wynne Hsu, Mong Li Lee. 2002).

RELATED WORK

Data Mining on Multimedia:

Multimedia data mining is used for extracting interesting information on multimedia data sets, such as audio, video, images, graphics, speech, text and combination of several types of data set which are all converted from different formats into digital media. Multimedia mining is a subfield of data mining which is used to find interesting information about implicit knowledge from multimedia databases. Multimedia data are classified into five types; they are (i) text data, (ii) Image data (iii) audio data (iv) video data and (v) electronic and digital ink. Text data can be used in web browsers, messages like MMS and SMS. Image data can be used in artwork and pictures with text still images taken by a digital camera. Audio data contains sound, MP3 songs, speech, and music. Video data include time-aligned sequence of frames, MPEG videos from desktops, cell phones, video cameras. Electronic and digital ink its sequence of time-aligned 2D or 3D coordinates of stylus, a light pen, data glove sensors, graphical, similar devices are stored in a multimedia database and use to develop a multimedia system as suggested by Vijayarani and Sakila (2015).

Multimedia is relating different media, e.g., text, imagery, video, animation, and sound, into one application, presenting these multiple media in an integrated way to communicate a message. Video is thought-provoking because by itself it can be measured a multimedia presentation. Consider a news broadcast that includes text overlays identifying people and place. One example is by means of a camera-phone to take the picture of a real-world object (e.g. a building or physical store) for which we would like to find information on the Web. The picture composed of a few words describing the user's information need can be jointly submitted to a search engine, and then the engine returns web pages covering information about that real-world object of the right context. This multimodal query (photo + keyword description) retrieves web pages that are more than one modality grounded on both image and text similarity. (as cited in Brett Adams, Dinh Phung, Svetha Venkatesh, 2006).

The high dimension of multimedia features makes the feature space very sparse, foremost to generalization errors. A rule of thumb is to use as much training data as possible, but in some applications, training data is itself sparse.

The applications of multimedia data mining, some of which are as follows:

Digital Library: The collection of digital data are stored and maintained in digital library, which is essential to convert different formats of digital data onto text, images, video, audio, etc.

Traffic Video Sequences: In order to determine important but previously unidentified knowledge from the traffic video sequences, the detailed analysis, and mining to be performed based on vehicle identification, traffic flows, and queue temporal relations of the vehicle at intersection. This provides an economic approach to regular traffic monitoring processes.

Medical Analysis: Multimedia mining is primarily used in the Medical field and particularly for analyzing medical images. Various data mining techniques are used for image classification. For example, Automatic 3D delineation of highly aggressive brain tumors, Automatic localization, and identification of vertebrae in 3D CT scans MRI Scans, ECG and X-Ray.

Customer Perception: It contains details of customers opinions, products or services, customers complaints, customers preferences, and the level of customer's satisfaction with products or services which is collected together. Many companies have to call centers that receive telephone calls from the customers. The audio data serves as topic detection, resource assignment, and evaluation of quality of services.

Media Making and Broadcasting: Radio stations and TV channels creates broadcasting companies and multimedia mining can be applied to monitor their content to search for more efficient approaches and improve their quality.

Surveillance system: It consists of collecting, analyzing, summarizing audio, video or audiovisual information about specific areas like government organizations, multi-national companies, shopping malls, banks, forest, agricultural areas and highways etc. The main use of this technology in the field of security hence it can be utilized by military, police and private companies since they provide security services is stated by Dr. S.Vijayarani and Ms. A.Sakila. (2015).

Temporal Data Mining on Multimedia data:

The amount of consumer-generated multimedia data onto the internet has grown almost exponentially in recent times. One popular multimedia upload site, YouTube, reported about a year ago that 300 hours of multimedia recordings are uploaded on it every minute in video youtube statistics. In real life, media information has time attributes either implicitly or explicitly. This kind of media data is called temporal data. Temporal data exist extensively on economic, financial, communication, and other areas such as weather forecast. Temporal databases store past, present and possibly future data. Temporal databases are append-only and current data values become historical data as new data values are added to the database. (as cited in Chelliah Balasubramanian, Karuppaswamy Duraiswamy, 2009).

A user can import photos, videos, and movies in the mentioned with the file format. Time of creation for each item is extracted

from the EXIF header of JPEGs, and thumbnails for videos created with digital cameras. Movie creation time is obtained from the file creation timestamp of the first shot. For users with audio logs, media items are tagged with position when available. If it is not available for the exact creation time of a media item, a widening neighborhood in time is searched. No attempt has been made to improve this annotation.

From a multimedia data processing perspective propose that these temporal data can be categorized into two kinds is suggested by D.Saravanan and K.Chokanathan. (2010),

Continuous variables: related to time points (a series of single measurement at particular moments in time)

Event variables: related to time intervals (e.g. the onset and offset of an event). For example, the location of an object in a video is a continuous temporal variable that may vary from time.

Clustering of temporal data involves grouping a collection of time series based on their similarity. It is the most frequently used technique in temporal data mining, as it can automatically find structures or patterns in large data sets that would be otherwise difficult to summarize (or visualize). Searching for sequences in large databases is another important task in temporal data mining. Sequence searches and retrieval techniques play an important role in interactive explorations of large sequential databases. The problem is concerned with efficiently locating subsequence's (often referred to as queries) in large archives of sequences (or sometimes in a single long sequence). The pattern discovery task of temporal data mining discovers all patterns of interest in a large dataset. The following are the Temporal Data Types is stated by Pughazendi.N, Punithavalli.M (2011).

Fully Temporal: It is time dependent. Data and information derived from it are completely dependent on time. Example: Transactional data in databases.

Time Series: This is a special case of time-stamped data. It is similar to a number line. The events are uniformly separated in time dimension. Time series and temporal sequences are seen in a variety of domains like engineering, research, medicine, and finance.

Time Stamped: It has explicit information related to time. Temporal distance between data elements can be found. Inferences made can be temporal or non-temporal. Example: data from stock exchange, inventory management.

Sequences: Sequences are ordered events with or without a concrete notion of time. Example: customer shopping sequences, biological sequences. If an event appears before another, it means that the former event has occurred before the latter.

The goal of temporal data mining is to find hidden relations between given sequence of events. An efficient approach to mining such relations is sequence mining. It involves three steps are stated by Amit Doshi, Kashyap Bhansali, Prof. Lynette D'Mello. (2014):

Transformation: converting given data into suitable form.

Similarity Measure: defining the similarity measures to be used.

Mining Operation: applying mining operation to get desired results.

Examples of application domains dealing with temporal data are suggested by Dr. S.Vijayarani and Ms. A.Sakila. (2015):

Financial Applications: e.g. history of stock markets, share prices

Reservation Systems: e.g. when was a flight booked

Medical Systems: e.g. patient records

Computer Applications: e.g. history of file backups

Archive Management Systems: e.g. sporting events, publications, and journals.

Need for Temporal Mining on Multimedia content:

Live News were captured in place with very weak network infrastructures and it is imperative that a citizen journalist can quickly and reliably upload videos in the face of slow, unstable, and intermittent Internet access is explained by Shah, R.R., M. Hefeeda, R. Zimmermann, K. Harris, C. H. Hsu, and Y. Yu. (2016). This envision that some middle boxes is deployed to collect these videos over energy-efficient short-range wireless networks. Multiple videos may need to be prioritized, and then optimally transcoded and scheduled. In this study, introduce an adaptive middlebox design, called NEWSMAN, to support citizen journalists. NEWSMAN jointly considers two aspects under varying network conditions: (i) choosing the optimal transcoding parameters, and (ii) determining the uploading schedule for news videos to design, implement and evaluate an efficient scheduling algorithm to maximize a user-specified objective function.

An event in two news stories is defined as a specific happening to a certain time, in a specific place and involves two or more number of participants. Different news articles look at the same occurrence through different point of views. Gathering information about the same or similar events from different news corpora poses a tricky and interesting challenge is stated by Gupta P. and Sharma A. K. (2010). In automatic summarization, events are ranked in documents. The Page Rank algorithm is the go-to tool for deciding the importance of events. The existing approaches have a couple of things working against them. Primarily, it is borderline impossible to extract elements from each event. Secondly, there is variance in the associative strength of events and event relations being depicted might suffer from a lack of accuracy. Based on the above discussion, it is observed that detecting "event instance" at sentence level from Web documents is a challenging task. Most of the above-stated methods have failed in understanding the semantics of "event instance".

Understanding the Metadata of Multimedia content:

A consortium of companies formed Metadata Working Group in 2006 or 2007. Version 2.0 of the specification was released

in November 2010, giving recommendations of, image metadata formats to refers to the standard protocols and techniques used to store image metadata within an image file. Three embedded image metadata formats EXIF, IPTC-IIM, and XMP are available. (is cited in Guidelines for Handling Image Metadata PDF)

EXIF

Exchangeable image file format (officially Exif, according to JEIDA/JEITA/CIPA specifications) is a standard that specifies the formats for images, sound, and ancillary tags used by digital cameras (including smartphones), scanners and other systems handling image and sound files recorded by digital cameras. The date and time of image creation tag was the temporal data, the standard is the date, and time the file was changed. The format is "YYYY: MM: DD: HH: MM: SS" with time shown in 24-hour format, and the date and time separated by one blank character [20.H]. When the date and time is unknown, all the character spaces except colons (":") may be filled with blank characters, or else the Interoperability field may be filled with blank characters. The character string length is 20 bytes including NULL for termination.(is cited in Digital Still Camera Image Metadata PDF) When the field is left blank, it is treated as unknown. Tags exist on EXIF format are,

- Manufacturer
- Model
- Orientation (rotation)
- Software
- Date and time
- YCbCr positioning
- Compression
- X resolution
- Y resolution
- Resolution unit
- Exposure time
- F-number
- Exposure program
- Exif version
- Date and time (original)
- Date and time (digitized)
- Components Configuration
- Compressed bits per pixel
- Exposure Bias
- Max. aperture value
- Metering mode
- Flash
- Focal length
- MakerNote
- FlashPix version
- Color space
- Pixel X dimension
- Pixel Y dimension
- File source
- Interoperability index
- Interoperability version

IPTC-IIM

The Information Interchange Model (IIM) is a file structure and set of metadata attributes that can be functional to text, images, and other media types. It was developed in the early 1990s by the International Press Telecommunications Council (IPTC) to accelerate the international exchange of news among newspapers and news agencies. The full IIM specification comprises a complex data structure and a set of metadata definitions. Although IIM was envisioned for use of all types of news items — including simple text articles — a subset found broad worldwide receiving as the standard embedded metadata used by news and commercial photographers. Information such as the name of the photographer, copyright information and the caption or other explanation can be embedded either manually or automatically. IIM metadata embedded in images is often denoted to as "IPTC headers", and can be easily encoded and decoded by most widely held photo editing software is stated in Information Interchange Model.

XMP

Extensible Metadata Platform (XMP) is an ISO standard, for the creation, processing, and swap for standardized and custom metadata for digital documents and data sets. XMP regulates a data model, a serialization format and core properties for the explanation and processing of extensible metadata. It also delivers guidelines on embedding XMP information about popular image, video, and document file formats, such as JPEG and PDF, without breaking their readability by applications that do not provision XMP. Therefore, the non-XMP metadata had to be reconciled with the XMP properties. Although metadata can instead be stored in a sidecar file, embedding metadata avoids problems that occur when metadata is stored separately.

XMP data model, serialization format, and core possessions is published by the International Organization for Standardization as ISO 16684-1:2012 standard. The defined XMP data model can be used to store any set of metadata possessions. These can be simple name-value pairs, organized values or lists of values. The data can be nested as well. The XMP standard also defines particular namespaces for defined sets of core possessions (e.g. a namespace intended for the Dublin Core Metadata Element Set). Custom namespaces can be used to extend the data model. An instance of the XMP data model is called a XMP packet. Adding possessions to a packet does not affect existing possessions. Software to add or modify possessions in a XMP packet should leave properties that are unknown to it untouched. (is cited in Elizabeth Gasiorowski-Denis 2012)

Dublin Core Metadata Element Set consists of 15 metadata elements:

- Creator
- Subject
- Description
- Publisher
- Contributor
- Date
- Type

- Format
- Identifier
- Source
- Language
- Relation
- Coverage
- Rights

For example, it is useful for recording the past of a resource as it passes through multiple processing steps, from being photographed, scanned, or authored as text, through photo editing steps (such as cropping or color adjustment), to accumulate into a final document. XMP allows each software program or device along the workflow to add its own information to a digital resource, which conveys its metadata along. Prerequisite is that all involved editors either dynamically support XMP, or at least do not delete it from the resource.

XMP can be used in several file formats such as PDF, JPEG, JPEG 2000, JPEG XR, GIF, PNG, WebP, HTML, TIFF, Adobe Illustrator, PSD, MP3, MP4, Audio Video Interleave, WAV, RF64, Audio Interchange File Format, PostScript, Encapsulated PostScript, and planned for DjVu. In a typical edited JPEG file, XMP information is typically included beside Exif and IPTC Information Interchange Model data is stated in Dublin Core Metadata Element Set weblog.

Clustering of digital photo collection based on timestamp:

For each photo, the EXIF headers are processed to extract the timestamp (if EXIF information is not available, rely on the modification time of the digital image file). The N photos in the collection are then ordered in time so the resulting timestamps,

$$\{t_n : n = 1, \dots, N\},$$

satisfy,

$$t_1 \leq t_2 \leq \dots \leq t_N.$$

Throughout, index the timestamps and the rows and columns of the similarity matrices by photo (in time order), not by absolute time. Temporal event clustering is unsupervised and involuntary and its performance approximates that of hand-tuned techniques (i.e. algorithms with thresholds that are manually set to optimize performance). The similarity-based framework presented below is very general. It can integrate content-based features and relevant metadata, and the multi-scale novelty features and examination can be applied to text, audio, and video stream segmentation.

Several variants of an automatic unsupervised algorithm to partition a collection of digital photographs based either on temporal similarity alone or on temporal and content-based similarity. First, inter-photo resemblance is quantified at multiple temporal scales to identify likely event clusters. Second, the final clusters are determined according to one of three clustering goodness criteria. The formulation based solely on temporal resemblance can be used to analyze any timestamped data collection. (as cited in Cooper, M., Foote, J., Girgensohn, A., and Wilcox, L. 2003)

Proposal – Temporal Mining on Files Algorithm

To improve image searches quality of temporal dynamics of image collections. In other words, given Web image collections associated with keywords of interest, aiming at identifying their characteristics temporal patterns of occurrences and leveraging them to improve search relevance to a query time. Problem is closely related to one recent emerging research in information retrieval of a personal computer (is cited in Gunhee Kim and Eric P. Xing, 2013) exploring the temporal dynamics of Web queries to improve search relevance. Many queries are time-sensitive, the popularity of a query and its most relevant documents change in time.

Temporal information is synergetic in image retrieval of a data warehouse or image storage environment of social media like Facebook, Instagram, ..., etc. If a query word has a broad range of concepts, its dominant usages vary much according to users. Our experiments show that once we can identify a user's preference, image retrieval can be further specific since the term usages of individual users are relatively stationary. Preliminary worked on depends on the properties termed to be metadata on file and performing the classification or clustering and reordering the image information.

Image file header as per metadata standard looks like below,

```
typedef struct _IMAGE_FILE_HEADER {  
    ...  
    DWORD TimeDateStamp; //32-bit time_t structure.  
    DWORD ModifiedTimeDateStamp; //32-bit time_t structure.  
    DWORD Pixel; // Resolution depth of image  
    ...  
} IMAGE_FILE_HEADER, *PIMAGE_FILE_HEADER;
```

Values of an image file created in Timestamp: Tue Aug 09 23:05:55 2017 and represented in DWORD as 41107CC3 is suggested by Omeed Kamal Khorsheed, 2014. Based on the above value as sample, a collection of images is processed in the following algorithm and

Algorithm: Temporal Mining on Files Algorithm (TMFA)

Input: Set of Images any format

Output: Classifying the images based on existence of temporal information

Step 1: Identifying the Image type

Step 2: Extract and sort image based on filename, resolution, timestamp of creation and modified

Step 3: For all each image taken

- a. Retrieve the header information on the file.
- b. Each header contains the information's like filename, Timestamp of creation, Timestamp of modification, tag names.
- c. Based on Timestamp of the file the class level is created.

d. Three sets of classification are identified with a file depending on filename, timestamp of creation and modification.

The image collections are classified based on three main types. Temporal representation of images will be classified like the below in figure 1 representation.

Step 4: Through the above step 2, all images is classified and three classification groups are listed.

The temporal information cluster is formed with into hierarchy of parameters year, month, day, hour, minute, second and filename is grouped the cluster groups looks alike below representation shown in Figure 2.

Step 5: Timestamp of Creation and modification gives a unique hierarchy and representing the contents.

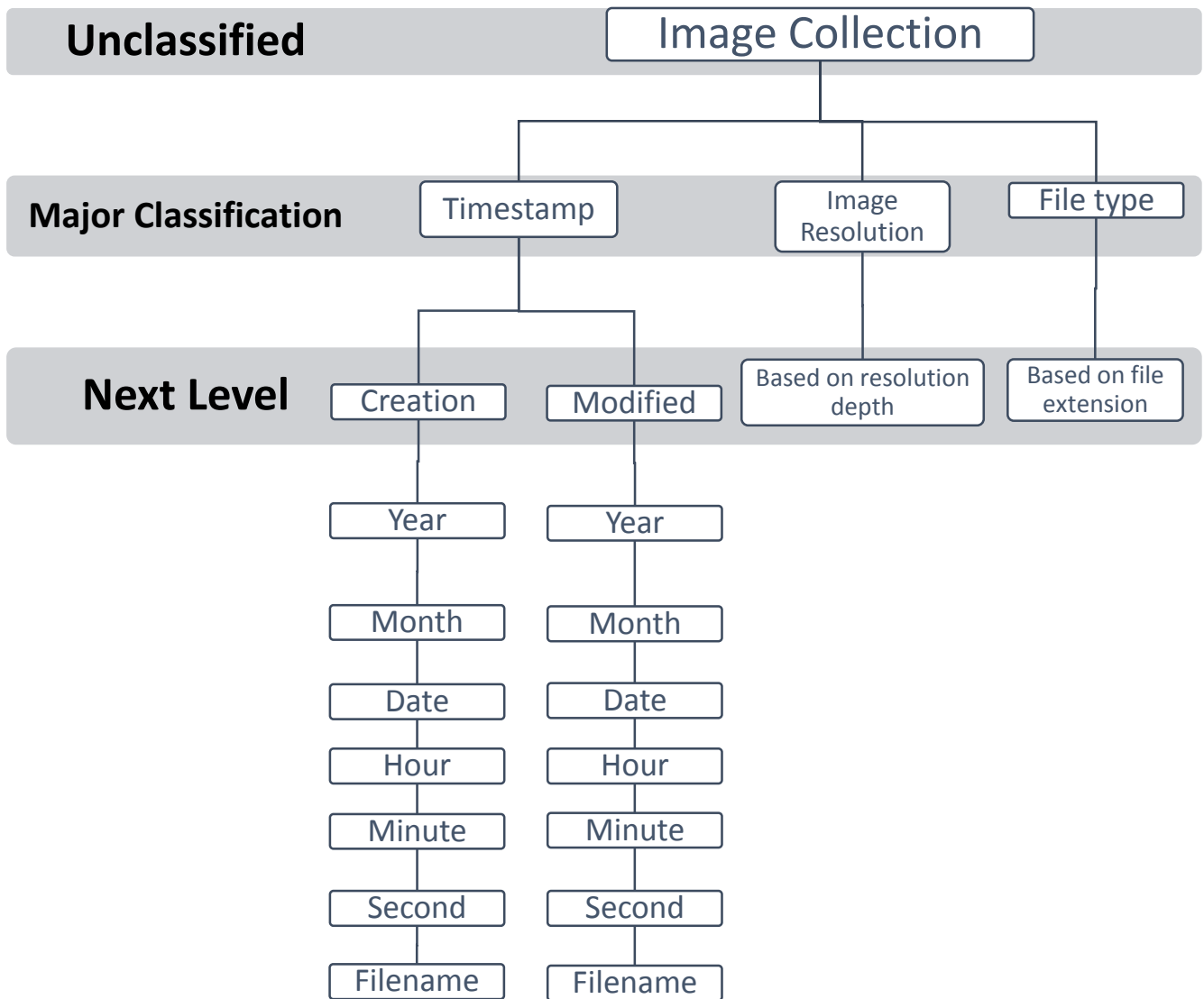


Figure 1: Hierarchy of Meta-Data based classification

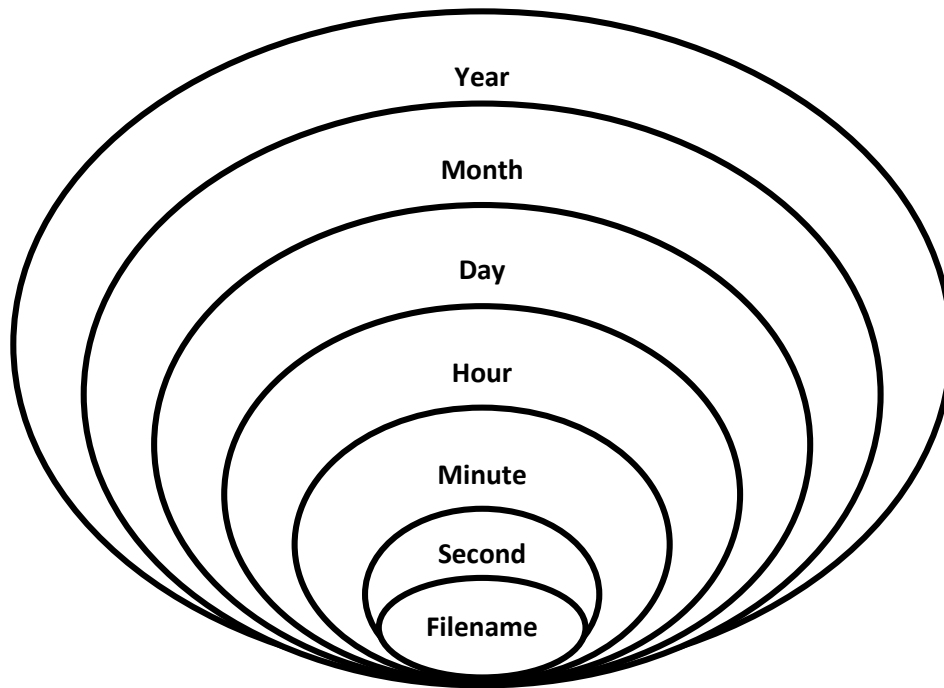


Figure 2: Hierarchy of Temporal-Data based classification

EXPERIMENTAL RESULT

Based on the above TMFA algorithm the following images about 100, 200, 300, 400, 500, 600, 700, 800 are taken for consideration for constructing a mining based classes. The unique achievement of number of class created based on the listed number of images considered.

Our sample hierarchal cluster representation in Figure 3 using TMFA algorithm implementation of 100 sample jpeg files meta information's timestamp with the above-mentioned hierarchy of file creation is visually represented in the following cluster form using JUNG framework is suggested in Java Universal Network/Graph. With hierarchy of Year – 2017 → Month – 8 → Day – 1 → Hour – 0,1,2,3 → Minute – 0 .. 60 → Second – 0 .. 60 → filename timestamp.

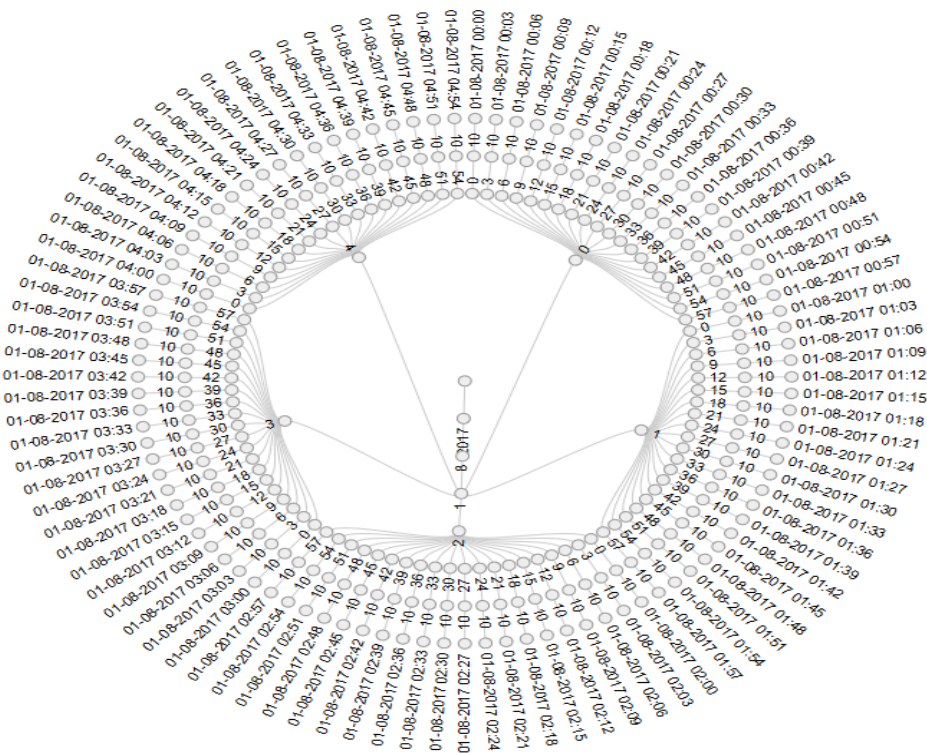


Figure 3: Clusters of sample files based temporal information

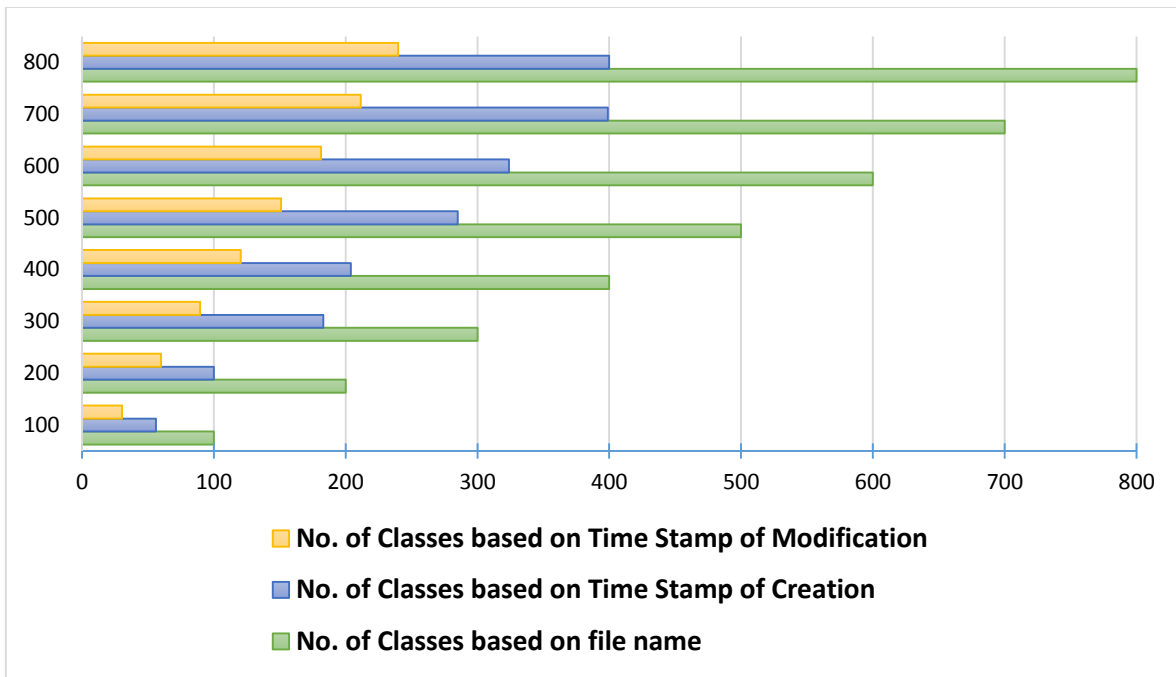


Figure 4: Comparison over number of Classes based on image metadata

Their variations in number of classes constructed towards timestamp of file created and file modified is highlighted after classification in the following figure 4 based on image properties with varying number of images like 100, 200, 300, 400, 500, 600, 700, 800 taken as sample.

CONCLUSION AND FUTURE WORK

The proposed work firstly uses the association to relate various items based on timestamp then classify them by the classification algorithm. The implementation is done by using the Java by fetching the timestamp of a file. The simulation result shows the comparison of the number of classes constructed based on properties of a file. A significant result is generated like the number of classes created through classification algorithm with filename is 46 % higher than number of classes created with Timestamp of creation and 69 % higher than number of classes created with Timestamp of modification. It means the performance of the proposed algorithm is better in constructing of classes based on timestamp. In future work, this classification can be extended to improve along with geotagging by provision the spatial-temporal mining on multimedia data's.

REFERENCE

- [1] Dr. S.Vijayarani and Ms. A.Sakila. (2015). Multimedia Mining Research –An Overview. *International Journal of Computer Graphics & Animation*, 5(1), 69-77.
- [2] D.Saravanan and K.Chokanathan. (2010). Visual Data Mining Framework for Video Data. *International Journal of Computer Communication and Information System*, 2(1), 209-212.
- [3] Ji Zhang, Wynne Hsu, Mong Li Lee. (2002). Image Mining: Trends and Developments. *Journal of Intelligent Information Systems*, 19(1), 7–23.
- [4] Sankar K.V, Uma.S, Subin.P.S, Ambat Vipin. (2014). A Literature Review on DataMining. *International Journal of Research in Computer Applications and Robotics*, 2(7), 95-101.
- [5] Pughazendi.N, Punithavalli.M (2011). Temporal Databases and Frequent Pattern Mining Techniques. *International Journal of P2P Network Trends and Technology*, 13-17.
- [6] Tzung-PeiHong, Guo-ChengLan, Ja-HwungSu, Pei-ShanWu, Shyue-LiangWang. (2016). Discovery of temporal association rules with hierarchical granular framework. *Applied Computing and Informatics*, 12(2), 134-141.
- [7] Omeed Kamal Khorsheed. (2014). A Review Search Bitmap Image for Sub Image and The Padding Problem. *International Journal of Advances in Engineering & Technology*, 684-691.
- [8] Brett Adams, Dinh Phung, Svetha Venkatesh. (2006). Extraction of Social Context and Application to Personal Multimedia Exploration. *14th Annual ACM International Conference on Multimedia*, Association for Computing Machinery, New York, 987-996.
- [9] Chelliah Balasubramanian, Karuppaswamy Duraiswamy. (2009). A mining method for tracking changes in temporal association rules from an encoded

database. International Journal on Computer Science and Engineering, 1(1), 1-8.

- [10] Amit Doshi, Kashyap Bhansali, Prof. Lynette D'Mello. (2014). Study of Temporal Data Mining Techniques. International Journal of Engineering Research & Technology, 3(10), 147-150.
- [11] Shah, R.R., M. Hefeeda, R. Zimmermann, K. Harras, C.-H. Hsu, and Y. Yu. (2016). NEWSMAN: Uploading Videos over Adaptive Middleboxes to News Servers In Weak Network Infrastructures. In *Proceedings of the Springer International Conference on Multimedia Modeling*, 100–113.
- [12] Gupta P. and Sharma A. K. (2010). Context-based indexing in search engines using ontology. International Journal of Computer Applications, 1(14).
- [13] Youtube statistics, <http://www.youtube.com/yt/press/statistics.html>
- [14] "Guidelines for Handling Image Metadata" (PDF), Metadata Working group. 2010-11-01, http://www.metadataworkinggroup.org/pdf/mwg_guidance.pdf.
- [15] Digital Still Camera Image File Format Standard (Exchangeable image file format for Digital Still Cameras: Exif) version 2.1. Retrieved from <http://web.archive.org/web/20131111073619/http://www.exif.org/Exif2-1.PDF>
- [16] Information Interchange Model (IIM) weblog (2014). Retrieved from <https://iptc.org/standards/iim/>
- [17] Elizabeth Gasiorowski-Denis (2012). Adobe Extensible Metadata Platform becomes an ISO standard. Message posted to <https://www.iso.org/news/2012/03/Ref1525.html>
- [18] Dublin Core Metadata Element Set weblog (2012). Retrieved from <http://dublincore.org/documents/dces/>
- [19] Gunhee Kim and Eric P. Xing. (2013). Time-sensitive web image ranking and retrieval via dynamic multi-task regression. In Proceedings of the sixth ACM international conference on Web search and data mining, ACM, New York, NY, USA, 163-172.
- [20] Cooper, M., Foote, J., Girgensohn, A., and Wilcox, L. (2003). Temporal event clustering for digital photo collections. In Proceedings of the eleventh ACM international conference on Multimedia, ACM, 364–373.
- [21] Java Universal Network/Graph (JUNG) Weblog (2010). Retrieved from <http://jung.sourceforge.net/applet/>