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Discovery of Non-Persistent Motif Mixtures using MRST (Multivariate Rhythm Sequence Technique)

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Abstract- In this paper we present a prototype to discover the unsupervised repeating temporary perception in a time series. The purpose of this work is to control the case of random variable and to find out the measurements caused by the phenomena of simultaneous synchronization. The proposed model has used the non-parametric Bayesian technique to trace the motifs and their occurrences in the data documents. We introduce the Multivariate Rhythm Sequence Technique (MRST) method to find the rebound and repeated motifs and their instance in every document automatically and simultaneously. This model is used in wide range of applications and concentrates on datasets from different modalities.

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Strictly as per the compliance and regulations of:

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R Kumar α & Capt. Dr. S Santhosh Baboo σ

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The video footages from non-dynamic cameras and data location bounded to the motif-mining server. The high semantic internal representation of the method gives advantage in operation such as event counting or analyse the scène. We used the sample images and videos from New York City traffic data for experiments with and the results shows better performance than the existing motif mixtures analysis in the time series.

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I. Introduction

Motif Mining is one of the active research area in recurrent temporal pattern in time series. The ultimate aim is to find out the small amount of repeating temporal pattern with little possible super vision in multiple variant time series. The super position analysis using various phenomena in time series is without synchronization. This work is to extractarious operations and activities in different domains from the video footage. Normally we get the video sequence consists different movements by various people or various objects present in the video footage. In this case we are using the long term recording to study the independent activities and their presence in the video automatically.

Time series motifs are recurrent segments in a long time series that their presence implies the precise information about the underlying source of the time series. Motif discovery in time series data has received significant attention in the data mining community since its inception, principally because, motif discovery is meaningful and more likely to succeed when the data is large.

Different types of the time series has the same characteristics of being unification of the multiple actions or motifs. Here we assume the time series pertaining to the electricity lining and consumption of the water in a particular building. In this experiment, we can find out the motif such as water consumption and short circuit in the building. It is also possible that we can find some other method to supply the water and electricity in the particular apartment. It is also possible to determine the consumption of water and electricity. This kind of multiple incidence of motifs happens at the same time without any synchronization.

To find out the specific activity patterns without supervision is our primary goal. The starting point of the task is to recap the scene, count or detect the specific scene to find with the unusual activity. Figure 1 explains the difference in the particular case without supervision video sequence.

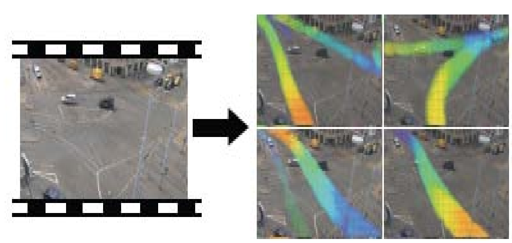

Figure 1(a) *Figure 1(b)*

Figure 1 is the result of the experiment on a video footage. 1(a) without supervision from which we are going to extract the temporary activity methods. 1(b) motif represented as time denoted by the gradient colour.

II. Related Work

Considering the non-parametric Bayesian technique, it is systematically investigating each of the implicit number of motifs and number of motif present in every document. This method validates the synthetic data. This method also used for other prediction efficient such as video sequence and other domains. [1]

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The video sequences are divided into simple clips in order to find the flow fields in that particular video sequences. Pixels has quantized based in the motion location and direction. This is a group of words denoted in the clips. Once we find the group of words, we can do the next state called as screening. This stage is to measure the words using the technique called "conditional entropy" after getting the result in full words, which are applied, to the diffusion map. Diffusion map is the framework, which has included the multiplex of the points into lower dimensional space while preserving the intrinsic local geometric pattern. [2]

Hierarchical Bayesian method combines three elements in a visual surveillance. Basic a) level visual aspect, b) uncomplicated atomic activities and c) communication. Atomic activities are modelled as distributions over low-level visual features, and interactions are modelled as distributions over atomic activities. This method uses unsupervised learning method. Taking a long video footage, movable points are clustered as various atomic activities and small video sequence shows the interactions. [3]

Unsupervised learning method relies on possibilities. Latent semantic analysis approach is used to set visual characteristics including the attributes like size and motion activities for finding same actions happening in the particular scenes. Then the patterns are found in the segments into regions is clear and activity content. [4]

We present two novel methods to automatically learn spatiotemporal dependencies of moving agents in complex dynamic scenes. They allow to discover temporal rules, such as the right of way between different lanes or typical traffic light sequences Systematically, the spatiotemporal dependencies of moving agents are observed in the in complex dynamic scenes. This scene allows to find out temporary protocols as the exact way between various lanes in the typical traffic areas. First model is based on the protocol based learning method. The next method uses Dependent Dirichlet Processes to learn an arbitrary number of infinite Hidden Markov Models. DDP-HMM. [5]. Different guessing based on kalman filter and non-argument regression are getting posterior inference in the topic. LDA is the Latent Dirichlet Algorithm method captures the data not only in the depressed concept data. We analysis how the architecture changes over the time. Here every method is related with the continuous distribution timestamps. Every document word generated by co-occurrence of the timestamp. [6][7]

A Markov clustering topic method is present to build in earlier method of dynamic Bayesian network method. Bayesian method has eliminated the draw backs about accuracy, strength and efficiency. Difficult dynamic clips by strength clustering visual activities correlates over the time. The Gibbs sampling is used for the offline and unlabelled data. [8]

LDA is used to find out the global correlation in the spread camera network LDA is used to divide the object action structure and local behaviour in every camera view first interference of the two local behaviours globally over the different camera views. The LDA is preparing to find out actions and temporal correlations. [9]

Latent Dirichlet Approach based method take the snap of the activities that changes over a period. The agglomerative based clustering on optical flow vectors in different angle and spatial information. Here every activity interrelates with not only in the distribution. It is interrelated with distribution over the timestamps. [10]

Normally every document has the combination of continuous motif activity and their starting appearance. Here they are using the three methods. First method has interrelated word at the particular time stamps and find out the word repeated in the document in the particular time series or temporal window. Second find the repeated action in the document. The third to find out the same occurrence and activity, which should be monitored. [11]

Bunch of data in each observation are grouped together in a mixture model. The number of colloid tools is known as unknown priori frequency from the data. This arrangement is known as the Dirichlet process the identified cluster property has provided the non-argument prior the number of composition of tools in each group.[12]

A structure of the non argument Bayesian method is known as the dual Hierarchical Dirichlet process. Unsupervised gravity discusses and semantic circle method in investigation settings. Heretrajectory is as the words in the document, which clusters into various activities. Defective words are identifying as sample with low probability. Semantic atmosphere sets way to get objects and relate the actions in the particular scene and creates the model of the scene. [13]

Global discourse method detects the abnormal activity that isolated appearance. Practical sector believe that kind of argument modulate is needed and real time is finagle. [14][15].

Using the activity trend has presence of instance to invoke similarity. Here no need of the inter camera registration or adjustment. However, apart from that system learn the camera network and possibilities of the path and instance in Parson Window at the time of training. When the training is finished related are assigned the maximum posterior the estimated structure. [16]

A cross-canonical correlation analysis structure detect and express the normal relationship in the two regional activities in the cross camera view. Find the spatial and network structure of the camera. Accurate and identify the person or object. Perform the activity segmentation collect the different camera views.[17]

Using the base level of the queue instance is finding in the each camera view independently and the landmark and speed of instance and trajectories are calculated as advantage. Generative method learns the actions and features in different camera sites. Grouping a same picture or image has convert into one cluster. Then all the cluster has find out from the different camera views and make it as a co- clustering has been published. [18]

III. Proposed Model

This proposed model MRST is to process the motif, number and occurrences. This section will explain three variations of the method called TAMM, VLTAMM and TSVLMM before going to the main concept in detail.

a) Background on Time Series Mrst Process

We introduce the Time Series of MRST Process, as a model, which handle the infinite mixture in the building, is our approach collusion components categorizes to the form of distributions. Here we are used the Gaussian mixture model to explain the concepts in the introduction part.

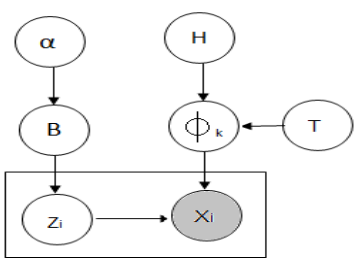


Figure 2 (a)

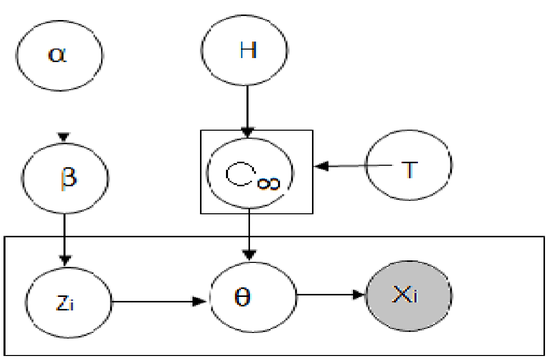


Figure 2 (b)

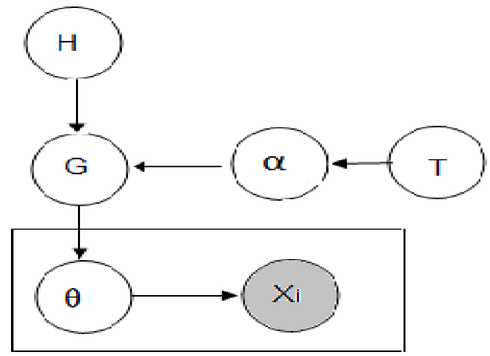


Figure 2 (c)

Figure 2 a) finite mixture with k elements with time t. b) Mixture representation with time t c) Compact representation of MRST.

The infinite number of mixture has an alternative delimited number with k and the time serial to accept this mixture nodes weight vector β as the length and α as the form. A α is the real number as argument and t is the time period while we are using the "stick breaking" method has given the infinite list of data that sum to 1.The weight vector $\beta_1 = \beta'_1$ is obtained from the beta distribution. The second weight vector in the same way $\beta_2=(T-\beta_1)*\beta'_1$ and so on this way is called as the stick breaking method.

Algorithm 1

getting the video sequence as INPUT

find video sequence ϕk (1)

find the time of the ϕk with time t

find the xi

convert into compact representation (2)

take it as ϕk in to ∞

calculate the ∞ with a time period t (3)

adding the θ value where θ =Z(i)* ∞ (4)

A concentrated equal node has been used to denote the time series MRST process. The mixture presentation has well acceptable derive the Gibs sampling method concentrated presentation is used in the broad manner to get a quick view of the model.

b) The Proposed Model

Our aim is to derive set of motifs a collection of record containing the index words. We define the record j is the group of experiment. {(w(ji) at(ji))}i=1...n(j) where w(j) words refer to the word book and the at(ji) is the at mean time of the experiment occurred in the document

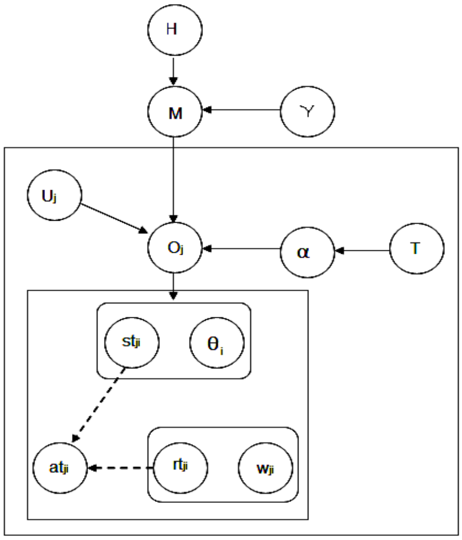


Figure 3(a)

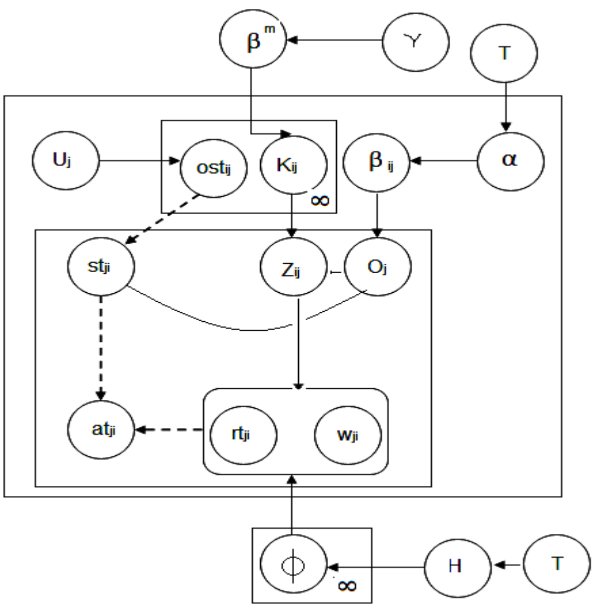


Figure 3(b)

Figure 3 represents the proposed models a) consolidate with MRST notation b) with develop time series MRST process and both levels.

Algorithm 2

get the video sequence with vector (5)

B(m) send to Ki where Ki is number of finite motif

B(i) from α when the time T (6)

find the ost multiple with U(j) where U(j) is possible of motifs (7)

O(j) * st(ij) where st(ij) is the founded possible motif

k(i)*Z(i) where Z(i) = convert the video sequence in to word

R(t)*W(t) =(∞*H*T) (8)

A(t)=R(t)*S(t) (9)

We look up the time details when defining the motifs temporal possibilities map. More importantly ϕk point the motif table and ϕk (w, RT) defines the possibility the word **w** presence at the relevant time object when the motif occurs (RT) is stated out aim is conclude the set of motifs more than one document. As per the early discussion it is compulsorily added to the every document. It is very difficult to find the number of motifs in advance so here we are using the time series MRST process which allows to read the number of variable in the motifs in the document.

Our new approach of the MRST process has use the graphical representation method shown in the figure 5.1 and 5.2. Consider the two diagrams the time series process notation has indicated by the group of square in the above diagram and the further method has used to find the variables and number of motifs in the time series of the document.

Here the settled relation is referring as the first MRST level which prepare the number of motifs from the ultimate combination M. Every motif has derived from an MRST process of distribution with argument N. Basic combination model has been LDA or HDP, the set of combination of the section is not only mutual information or document but also across the MRST using the second level commonly the document specification displacement O(j) is not consider the motif mixture.

Observations (w_{ji}, at_{ji}) are produced by the repeated sampling motif using the motif θ_{ji} to sample the word and its relevant time and motif. Using the sampling start time at(ji) absolute time st(ji)can be reduced. The developed method given in fig 4bit helps to understand the creation process.

The important difference in this small scale model is the way of the repentance as created is represented explicitly. Occurrence of the table Chinese restaurant model document specific is used to create the examples.

c) *Modeling Prior H And Motif Length In A Time*

The earlier section shows the worldwide structure of the method specially simplified the explanation of the superior H and neglect the details

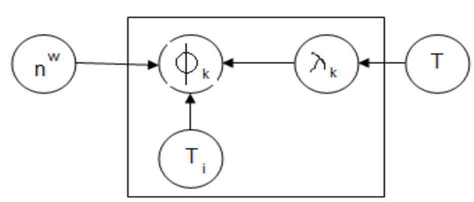
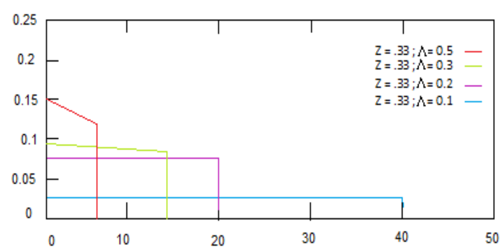


Figure 4

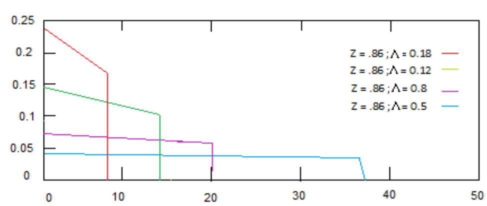
Figure: 4 different variable lengths have taken care of the various motif lengths according to time period.

The first method uses the finite motif length. The method of the paper created to allow the various motifs length of each is automatically has variable length temporal analysis of motifs that derived from the model 1 as the TAMM temporal analysis of motif mixture which is the important setting of the hyper arguments.

TAMM is the fixed duration so we are adding the variable time in t(i) to above model diagram so that it can be easily find out the motifs in the various time sequence. The hyper argument has variation so that we can find out easily in the secular time stamps or time periods. Here the influences of the variability surround this variation expectation. A huge weight of the result is less variability. Define the possibility of the words uniformly given and eliminate the size of the shape is the main role. However reduce the shape acts the important role in the interference.



Graph 1



Graph 2

Graph 1 & 2 shows the weight truncated distribution with different values and exponential rate. This is used to control the size of the slope in the particular time period.

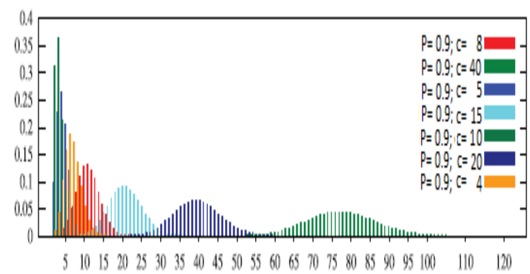
A Gama distribution with arguments (T=T1,T2) is used as the earlier argument of every motif. It must to be corrected Gama conjugate with the weight in the truncated distribution. Argument lambda and Z is fixed. This conjugate condition in the face of the L (lambda and Z) is greater than analysed from the truncated exponential distribution. It is represented as the following expression

IV. Inference

Here we are going to explain the stages about the inference. A pass over the stage executable for the VLTMM and TAMM method will be performed publically. To perform the inferences uses the confused Gibs sampling {oji, kjo, ostjo, ƛk}. The balance variable has logical integrating sampling and can integrate the motifs in their self used as H in the time series TRVSPT process distribution.

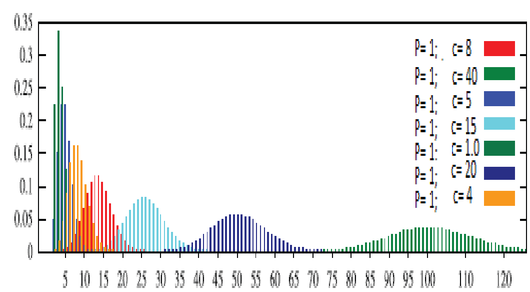
According to the sampling possibility organize and observer the mention earlier appearance is propositional to the two quantities. The first quantity is according to the MRST and CRP on the appearance and related to the number of repentance associated in the occurrence. The next step has to be comes in the likelihood of the particular observation then its virtual association and in the particular repentance.

The different method to crate the new repentance for this example is the Chinese restaurant process as its inverse to α. This possibility of the repentance is the inverse of the likelihood observation to the control of the hypothesis joined with random repentance. The linear process has all starting time control to integrate the initial time. Here we have a MRST and motif already as in the above example the possibility has inverse to the occurrence of the counting. Conjugate the MRST distribution H over motifs. We control to integrate the finding of motifs drawn to H as in Graph 3.



Graph 3

Distribution of the number of mixture elements sufficient to cover a proportion P of the total weight



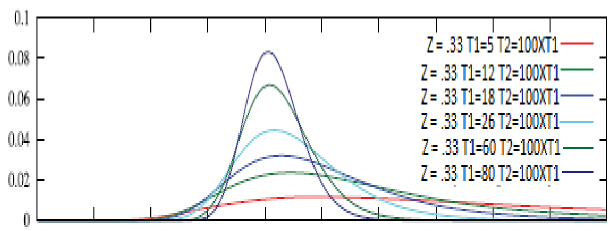
Graph 4

Distributions are shown for different concentration c and proportions P (90 and 95 percent)

V. Meaning and Settings of Parameter

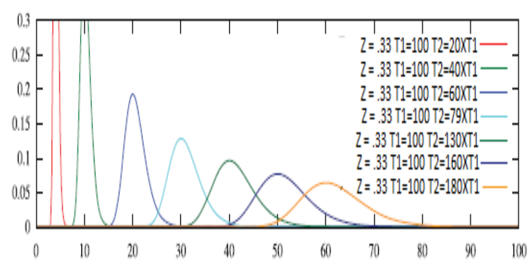
In our model we are using the different various arguments that can set to the influence of the inference. According to VLTAMM method has taken the arguments in hierarchal manner of the TAMM the argument has directly converted into the number of motifs. The isolation of the parameter gets the more important. So that controls the number of repentance in a document that might depend on the documents duration. Examples taking from the Gibs sampling method are to get the data and large amount of the data repeated or overlap in the particular time frame. The consequences are data set independent of the document and take the reference the small values.

The fixed weight truncation Z is the structure argument for weight truncation method. It manages the structure of the temporal in the motif. Weight exponential method is less support. To choose Z value considers the q ratio in between the values of the distribution.



Graph 5

Maximum motif length: Distribution of maximum motif length Lk; Z when varying the prior _ and keeping the parameter Z fixed



Graph 6

T can be used to control the location and spread of the range of prior acceptable values for Lk; Z.

VI. Video Data Analysis

Our method explains the experiments about the video data. Here we show the temporal documents from the input video talking about the temporal timing duration and method aspects of our model. Also establishes the interest and result of model time in the motif by comparing the results with other methods.

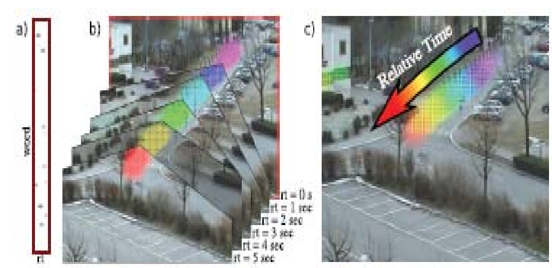
a) *Videos Convert To Temporal Document*

Created temporal documents has extracted the number of words at every time. Time step for the impermanent document use the pixel resolution for one second. One method will be our vocabulary directly using to low level. Result in a huge vocabulary with heavy temporal leads to a high disturbance computing load we capture the data in the low level feature of co-occurrence and convert to high level word. To eliminate the confusion about the notation use the super script in the word from the low-level layer.

In the first stage of feature extraction we have to extract the flow feature of the optical dense image grid. We place or store the pixels where the motion could be happened or detected. We divide the quantize in to nine categories of one to eight commonly quantize the flow of direction to prepare the slow motion. The low level character has used to define the position and image motion category. The size of the low level word should be high but however we reduce the words in to nearly 25000 words. Because we are considering the words only we run the slid window for second five to forty frames to get depending on the data set without dead lock and collect every time stamp in the particular window.

Details on dimensionality reduction getting the set of document have to be applied the probabilistic latent semantic method. This method takes the input words and count every document learn the set of data words by the defined distribution on low level word to corresponding to the soft cluster words that repeated words in the document. Scene has fixed here because we are reduced the dimensionality reduction.

PLSA method is the entire processes of this stage learns the new video documents and give the decomposition of the every document mixture of the earlier method the topic weights given by the distribution. We are use this data reweighted by according to the activity use to build the documents constitute the input method.



Divided in to two five-second motifs.

Figure 5

Here the video is factorized to full length and it is divided into the possible motifs and to full duration of the time motif. At last the motif duration has been increased and recovers the motif properly.

Use of the motif duration arguments VLTAMM provides the approach to deal with the short coming of the fixed motif duration. Variable length with motif duration with VLTAMM shows the sum of the result.

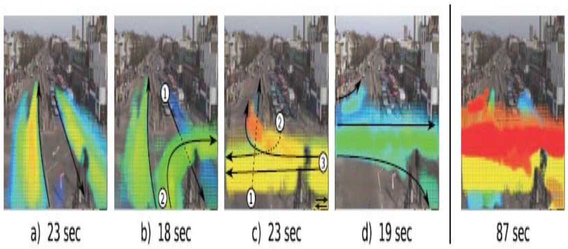


Figure 6: This figure shows how the junction data is analyzed by VLTAMM in a real time activity

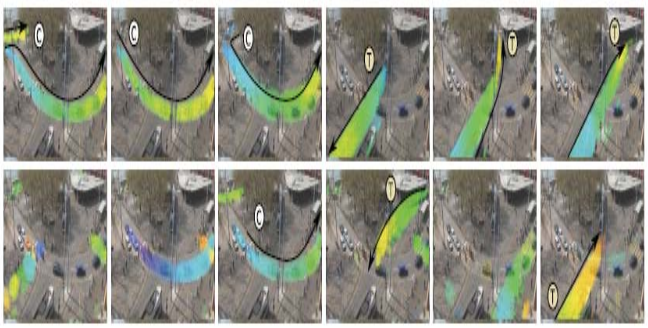


Figure 7: This shows motif is the 98 percentage of the observation one car coming from the left image and take the right direction of the road. 2 cars going the straightway and 3 cars taking the top turn, 4 car move from the traffic light it is the all motif taking at the different plane

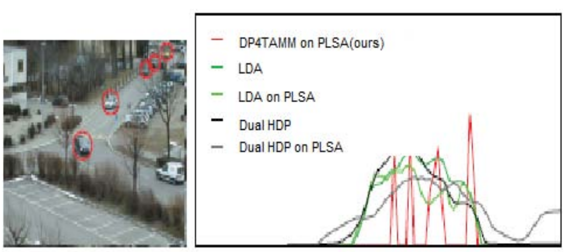


Figure 8

Figure 9 shows difference of the present and selected motif consider in the car activity. That image coming from the figure 8.

Activity diary and abnormality reporting is used to find the real motif when they occur at the real time. Here we take the example for the length of the video of 30 minutes and extract the motif and find out the motif time in the particular video scene. After getting the scene combine together and find out the motif occurrence.

VII. Comparison with Other Types

One disadvantage of other existing method is the difficulty to find out the motif and it's recurrent. Were as to find the temporal document ahs to be build the independent documents in the information is neglected here using LDA HDP-LDA. PLSA is used for the process method but using long temporal window it has neglected the time ordering to recover the motif and do not carry the temporal information and temporal granularity noise of the video.

The second model is time order sensitive LDA, here same slide window use the modification Cartesian product the original vocabulary and relative time within the particular window. The issue of this model are documents considering only in the independent and there is no necessity to align the data with the original activities in the video. So that the real time activity assume happen at different places. Our approach doesn't have any disadvantage compare to the above methods. Our method has store the temporal data independent and starting of their time of the actual scene of the video.

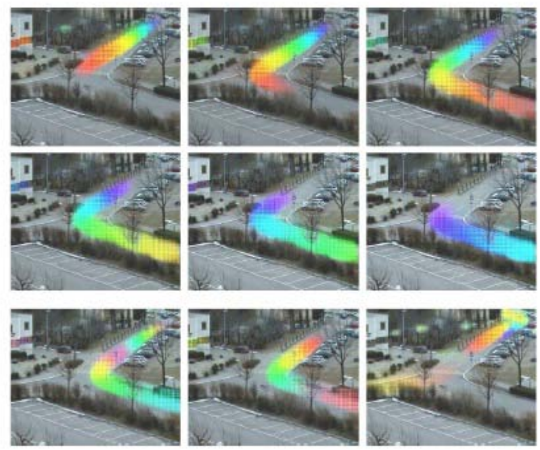


Figure 9: It shows the different activity and temporal activity at different time of the real scene

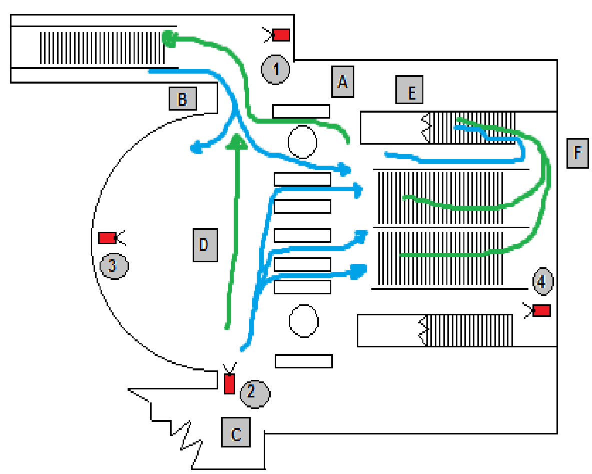


Figure 10: Architectural of the process to find the location to analyse the video samples and camera locations

a) Analysis of Multi camera calibration

To capture the images at the different camera position to analyse the temporal dependencies, the process use more number of cameras to integration method and join the all camera image and process the low level features using the low level count matrix. Low level camera calibration has the possibility to take large amount space because of the different camera view, we are using the three hundred or high level motifs. Low level support in the normal camera view suppose the overhead as in the camera 2 and camera 2 low level method has span the camera and make it as the two view and choose the nosily view and random occurrence. This activity has solved if larger amount of training data has used in this example

Recovered motif in multi camera these motif has resent the 78 percentage of the observation has find the actions and find the activity capture automatically.

Evaluation of the timing information has arises at the time that matches the original timing of the real image. But it is the problem to find out the different camera our model has find out very easily it recover the people activity between the two camera views. The start and end projection has displayed in the motif background process. Then we can easily calculate the difference between the original image activity and the motif representation.

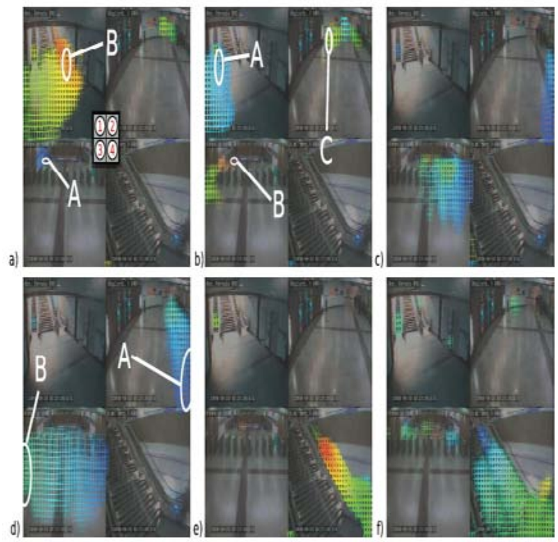


Figure 12

Figure 12 visual of the different camera views this map has taken from the metro activities. Here camera has capture the motif and who enter in the station and who are all comes out from the station has taken and clipped by the different camera angle and it represent the motif at the time level duration.

For example the result we are taken from the station about nearly two hours of unlabeled scenes.

Table 1: shows the recover the motif from the typical path duration during the experiment

Path		Measured Duration					Duration Motif
Motif	Start end	average	std	min	max	median	motif
A	a-b	26	2.8	30	32	28	24
B	a-b	28.5	5.2	25	43	27	22
C	a-c	19.9	9.0	15	38	18	12
D	a-b	9.5	1	9	16	8.5	6

Recover motif has compared and the presence of the repentance is extract these data has used to remove the multiple sequence of the data motif and convert the low level into high level of the motif using in the larger data. So that the repentance should be very high. The place of the track let information decrees the suspicious matches.

VIII. Conclusion

This model shown is new concept of finding the redundant temporal patterns in the particular time series. This method has used to find the joint and repeating motifs in the particular document. Identify how many common motifs present in the document and number of times motif occur in the document and also estimate the motif duration.

This method has validated the broad range of the data set and real time activity like traffic signals, micro phone pair, and video data's. Here we explained that the video data is activities in the traffic signals such as the movement of the car and typical person in the metro train station. Apply the simultaneous image on different camera view information without any calibration.

Audio signal coming from the two microphones in our model has used to recover the interest activities and yielded detection and precision. Using the artificial data assuming the robust model in the various hyperactive parameters has produced the meaning full information at the various situation applied in the variety of the data with success rate.

IX. Future Work

In future, this proposed model can be improved at the different levels to find the repeating values but it is not applied on the global activities. Suppose we are using the traffic signals we have to incorporate the heterogeneous methods to find out the recurrent motifs detection approaches. Then we will emphasise the different cycles of motifs and relation data for discover patterns. To scale up the input camera footage polynomial data will be concentrated in the upcoming approaches in time series.

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