

# Smart Surveillance: A Review & Survey Through Deep Learning Techniques for Detection & Analysis

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## Abstract

Big data applications are consuming most of the space in industry and research area. Among the widespread examples of big data, the role of video streams from CCTV cameras is equally important as other sources like social media data, sensor data, agriculture data, medical data and data evolved from space research. Surveillance videos have a major contribution in unstructured big data. CCTV cameras are implemented in all places where security having much importance. Manual surveillance seems tedious and time consuming. Security can be defending in different terms in different contexts like theft identification, violence detection, chances of explosion etc. In crowded public places the term security covers almost all type of abnormal events. Among them violence detection is difficult to handle since it involves group activity. The anomalous or abnormal activity analysis in a crowd video scene is very difficult due to several real world constraints. The paper includes a deep rooted survey which starts from object recognition, action recognition, crowd analysis and finally violence detection in a crowd environment. Majority of the papers reviewed in this survey are based on deep learning technique. Various deep learning methods are compared in terms of their algorithms and models. The main focus of this survey is application of deep learning techniques in detecting the exact count, involved persons and the happened activity in a large crowd at all climate conditions. Paper discusses the underlying deep learning implementation technology involved in various crowd video analysis methods. Real time processing, an important issue which is yet to be explored more in this field is also considered. Not many methods are there in handling all these issues simultaneously. The issues recognized in existing methods are identified and summarized. Also, future direction is given to reduce the obstacles identified. The survey provides a bibliographic summary of papers from Science-direct, IEEE Xplore and ACM digital library.

**Keywords:** Big Data, Video Surveillance, Deep Learning, Crowd Analysis.

## 1. Introduction

Analysis of surveillance videos involves a series of modules like object recognition, action recognition and classification of identified actions into categories like anomalous or normal. This survey giving specific focus on solutions based on deep learning architectures. Among the various architectures in deep learning, commonly used models for surveillance analysis are CNN, auto-encoders and their combination. Video surveillance systems-current status and future trends compares more than 100 papers published in the area of surveillance analysis. The paper begins with identifying the main outcomes of video analysis. Application areas where surveillance cameras are unavoidable are discussed.

Current status and trends in video analysis are revealed through :

Unsupervised sequential outlier detection with deep architectures.

- High-level feature extraction for classification and person re-identification.
- An ensemble of invariant features for person reidentification.
- Facial expression recognition using salient features and convolution neural network.
- Deep reconstruction models for image set classification.
- Crowd behavior analysis from fixed and moving cameras.
- Zero-shot crowd behavior recognition.
- The analysis of high density crowds in videos.
- Computer vision based crowd disaster avoidance system: a survey.
- Deep learning for scene-independent crowd analysis.
- Fast face detection in violent video scenes.

- Rejecting motion outliers for efficient crowd anomaly detection.
- Crowded scene understanding by deeply learned volumetric slices.

## 2. Literature Survey/Review

Finally, the vital points which need more consideration in near future are explicitly stated. Surveillance Video Analysis: Relevance in present world. The main objectives identified which illustrate the relevance of the topic are listed out below.

- Continuous monitoring of videos is difficult and tiresome for humans.
- Intelligent surveillance video analysis is a solution to laborious human task.
- Intelligence should be visible in all real world scenarios.
- Maximum accuracy is needed in object identification and action recognition.
- Tasks like crowd analysis are still needs lot of improvement.
- Time taken for response generation is highly important in real world situation.
- Prediction of certain movement or action or violence is highly useful in emergency situation like stampede.
- Availability of huge data in video forms.

The majority of papers covered for this survey give importance to object recognition and action detection. Some papers are using procedures similar to a binary classification that whether action is anomalous or not anomalous. Methods for Crowd analysis and violence detection are also included. Major part in existing work provides solutions specifically based on the context.

- Traffic signals and main junctions
- Residential areas
- Crowd pulling meetings
- Festivals as part of religious institutions
- Inside office buildings

Among the listed contexts crowd analysis is the most difficult part. All type of actions, behavior and movement are needed to be identified. Surveillance video data as Big Data Big video data have evolved in the form of increasing number of public cameras situated towards public places. A huge amount of networked public cameras are positioned around worldwide. A heavy data stream is generated from public surveillance cameras that are creatively exploitable for capturing behaviors. Considering the huge amount of data that can be documented over time, a vital scenario is facility for data warehousing and data analysis. Only one high definition video camera can produce around 10 GB of data per day. The space needed for storing large amount of surveillance videos for long time is difficult to allot. Instead of having data, it will be useful to have the analysis result. That will result in reduced storage space. Deep learning techniques are involved with two main components; training and learning. Both can be achieved with highest accuracy through huge amount of data. Main advantages of training with huge amount of data are listed below. It's possible to adapt variety in data representation and also it can be divided into training and

testing equally. Various data sets available for analysis are listed below. The data-set not only includes video sequences but also frames. The analysis part mainly includes analysis of frames which were extracted from videos. So, data-set including images are also useful. Methods identified/reviewed other than deep learning Methods identified are mainly classified into two categories which are either based on deep learning or not based on deep learning. This section is reviewing methods other than deep learning. SVAS deals with automatic recognition and deduction of complex events. The event detection procedure consists of mainly two levels, low level and high level. As a result of low level analysis people and objects are detected. The results obtained from low level are used for high level analysis that is event detection. Threshold Model used for spatial-temporal motion analysis and Bag of Actions for reducing search space Used for event detection of surveillance domain.

Five Modules for learning :-

- Event Model Learning
- Action Model Learning
- Action Detection
- Complex Event Model Learning
- Complex Event Detection

Interval-Based Spatial-Temporal Model (IBSTM) is the proposed model and is a hybrid event model. Other than this methods like Threshold models, Bayesian Networks, Bag of actions and Highly cohesive intervals and Markov logic networks are used. SVAS method can be improved to deal with moving camera and multi camera data set. Further enhancements are needed in dealing with complex events specifically in areas like calibration and noise elimination. Multiple anomalous activity detection in videos is a rule based system. The features are identified as motion patterns. Detection of anomalous events are done either by training the system or by following dominant set property. The concept of dominant set where events are detected as normal based on dominant behavior and anomalous events are decided based on less dominant behavior. The advantage of rule based system is that easy to recognize new events by modifying some rules.

The main steps involved in a recognition system are :-

- Pre Processing
- Feature Extraction
- Object Tracking
- Behavior Understanding

As a Pre-Processing system video segmentation is used. Background modeling is implemented through Gaussian Mixture Model (GMM). For object recognition external rules are required. The system is implemented in Matlab 2014. The areas were more concentration further needed are doubtful activities and situations where multiple object overlapping happens. Mining anomalous events against frequent sequences in surveillance videos from commercial environments focus on abnormal events linked with frequent chain of events. The main result in identifying such

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events is early deployment of resources in particular areas. The implementation part is done using Matlab, Inputs are already noticed events and identified frequent series of events. The main investigation under this method is to recognize events which are implausible to chase given sequential pattern by fulfilling the user identified parameters. The method is giving more focus on event level analysis and it will be interesting if pay attention at entity level and action level. But at the same time going in such granular level make the process costly. Video feature descriptor combining motion and appearance cues with length invariant characteristics is a feature descriptor. Many trajectory based methods have been used in abundant installations. But those methods have to face problems related with occlusions. As a solution to that, feature descriptor using optical flow based method. As per the algorithm the training set is divided into snippet set. From each set images are extracted and then optical flow are calculated. The covariance is calculated from optical flow. One class SVM is used for learning samples. For testing also, same procedure is performed. The model can be extended in future by handling local abnormal event detection through proposed feature which is related with objectiveness method. Multiple Hierarchical Dirichlet processes for anomaly detection in Traffic is mainly for understanding the situation in real world traffic. The anomalies are mainly due to global patterns instead of local patterns. That include entire frame. Concept of super pixel is included. Super pixels are grouped into regions of interest. Optical flow based method is used for calculating motion in each super pixel. Points of interest are then taken out in active super pixel. Those interested points are then tracked by Kanade– Lucas–Tomasi (KLT) tracker. The method is better the handle videos involving complex patterns with less cost. But not mentioning about videos taken in rainy season and bad weather conditions. Intelligent video surveillance beyond robust background modeling handle complex environment with sudden illumination changes. Also, the method will reduce false alerts. Mainly two components are there. IDS and PSD are the two components. First stage intruder detection system will detect object. Classifier will verify the result and identify scenes causing problems. Ten in second stage problematic scene descriptor will handle positives generated from IDS. Global features are used to avoid false positives from IDS. Tough the method deals with complex scenes, it does not mention about bad weather conditions. Towards abnormal trajectory and event detection in video surveillance works like an integrated pipeline. Existing methods either use trajectory based approaches or pixel based approaches. But this proposal incorporates both methods.

Proposal include components like :-

- Object and Group Tracking
- Grid Based Analysis
- Trajectory Filtering
- Abnormal Behavior Detection using Actions Descriptors

The method can identify abnormal behavior in both individual and groups. The method can be enhanced by adapting it to work in real time environment. RIMOC: a feature to discriminate unstructured

motions: application to violence detection for video surveillance. There is no unique definition for violent behaviors. That kind of behaviors show large variances in body poses. The method works by taking the exigent values of histograms of optical flow. The input video undergoes dense sampling. Local spatial-temporal volumes are created around each sampled point. Those frames of STV are coded as histograms of optical flow. Exigent values are computed from this frame. The papers already published in surveillance area span across a large set.

The methods already described and listed are able to perform following steps :-

- Object detection
- Object discrimination
- Action recognition

But these methods are not so efficient in selecting good features in general. The lag identified in methods was absence of automatic feature identification. That issue can be solved by applying concepts of deep learning. The evolution of artificial intelligence from rule based system to automatic feature identification passes machine learning, representation learning and finally deep learning. Real-time processing in video analysis Real time Violence Detection Framework for Football Stadium comprising of Big Data Analysis and deep learning through Bidirectional LSTM predicts violent behavior of crowd in real time. The real time processing speed is achieved through SPARK frame work. The model architecture includes Apache spark framework, spark streaming, Histogram of oriented Gradients function and bidirectional LSTM. The model takes stream of videos from diverse sources as input. The videos are converted in the form of non-overlapping frames. Features are extracted from this group of frames through HOG FUNCTION. The images are manually modeled into different groups. The BDLSTM is trained through all these models. The SPARK framework handles the streaming data in a micro batch mode. Two kinds of processing are there like stream and batch processing. Intelligent video surveillance for real-time detection of suicide attempts is an effort to prevent suicide by hanging in prisons. The method uses depth streams offered by an RGB-D camera. The body joints' points are analyzed to represent suicidal behavior. Spatial-temporal texture modeling for real-time crowd anomaly detection. Spatial-temporal texture is a combination of spatial-temporal slices and spatial-temporal volumes. The information present in these slices are abstracted through wavelet transforms. A Gaussian approximation model is applied to texture patterns to distinguish normal behaviors from abnormal behaviors.

Deep convolution framework for abnormal behavior detection in a smart surveillance system includes three sections :-

- Human subject detection and discrimination
- A posture classification module
- An abnormal behavior detection module

The models used for above three sections are, Correspondingly

- You only look once (YOLO) network

- VGG-16 Net
- Long short-term memory (LSTM)

For object discrimination Kalman filter based object entity discrimination algorithm is used. Posture classification study recognizes 10 types of poses. RNN uses back propagation through time (BPTT) to update weight. The main issue identified in the method is that similar activities like pointing and punching are difficult to distinguish. Detecting Anomalous events in videos by learning deep representations of appearance and motion proposes a new model named as AMDN. The model automatically learns feature representations. The model uses stacked de-noising auto encoders for learning appearance and motion features separately and jointly. After learning, multiple one class SVM's are trained. These SVM predict anomaly score of each input. Later these scores are combined and detect abnormal event. A double fusion framework is used. The computational overhead in testing time is too high for real time processing. A study of deep convolution auto encoders for anomaly detection in videos pro poses a structure that is a mixture of auto encoders and CNN. An auto encoder includes an encoder part and decoder part. The encoder part includes convolution and pooling layers, the decoding part include de convolution and unpool layers. It allows a combination of low level frames with high level appearance and motion features. Anomaly scores are represented through reconstruction errors. Going deeper with convolution suggests improvements over traditional neural network. Fully connected layers are replaced by sparse ones by adding sparsity into architecture. The paper suggests for dimensional reduction which help to reduce the increasing demand for computational resources. Computing reductions happens with  $1 \times 1$  convolutions before reaching  $5 \times 5$  convolutions. The method is not mentioning about the execution time. Along with that not able to make conclusion about the crowd size that the method can handle successfully. Deep learning for visual understanding: a review, reviewing the fundamental models in deep learning. Models and technique described were CNN, RBM, Auto encoder and Sparse coding. The paper also mentions the drawbacks of deep learning models such as people were not able to understand the underlying theory very well. Deep learning methods other than the ones discussed above are listed in the following methods reviewed in above sections are good in automatic feature generation. All methods are good in handling individual entity and group entities with limited size. Majority of problems in real world arises among crowd. Above mentioned methods are not effective in handling crowd scenes. Next section will review intelligent methods for analyzing crowd video scenes. Review in the field of crowd analysis The review include methods which are having deep learning background and methods which are not having that background.

Spatial temporal convolution neural networks for anomaly detection and localization in crowded scenes shows the problem related with crowd analysis is challenging because of the following reasons:-

- Large number of pedestrians

- Close proximity
- Volatility of individual appearance
- Frequent partial occlusions

Deep learning model Algorithms to be used:-

- A deep convolution neural network for video sequence background subtraction
- CNN
- SuBSENSE algorithm
- Flux Tensor algorithm
- Tracking people in RGBD videos using deep learning and motion clues

Deep Convolution Neural Network and Probabilistic Tracking Algorithm.

- Deep CNN based binary hash video representations for face retrieval
- Deep CNN
- Low-rank discriminating binary hashing, back-propagation (BP) algorithm
- DAAL: deep activation-based attribute learning for action recognition in depth videos
- 1D temporal CNN, 2D spatial CNN, 3D volumetric CNN
- Deep activation-based attribute learning algorithm (DAAL)

The paper suggests optical flow based solution. The CNN is having eight layers. Training is based on BVLC cafe. Random initialization of parameters is done and system is trained through stochastic gradient descent based back propagation. The implementation part is done by considering four different datasets like UCSD, UMN, Subway and finally U-turn. The details of implementation regarding UCSD includes frame level and pixel level criterion. Frame level criterion concentrates on temporal domain and pixel level criterion considers both spatial and temporal domain. Different metrics to evaluate performance includes EER (Equal Error Rate) and Detection Rate (DR). Online real time crowd behavior detection in video sequences suggests FSCB, behavior detection through feature tracking and image segmentation.

The procedure involves following steps:-

- Feature detection and temporal filtering
- Image segmentation and blob extraction
- Activity detection
- Activity map
- Activity analysis
- Alarm

The main advantage is no need of training stage for this method. The method is quantitatively analyzed through ROC curve generation. The computational speed is evaluated through frame rate. The data set considered for experiments include UMN, PETS2009, AGORASET and Rome Marathon. Deep learning for scene independent crowd analysis proposes a scene independent method which include following procedures:-

- Crowd segmentation and detection

- Crowd tracking
- Crowd counting
- Pedestrian travelling time estimation
- Crowd attribute recognition
- Crowd behavior analysis
- Abnormality detection in a crowd

Attribute recognition is done through a slicing CNN. By using a 2D CNN model learn appearance features then represent it as a cuboid. In the cuboid three temporal filters are identified. Ten a classifier is applied on concatenated feature vector extracted from cuboid. Crowd counting and crowd density estimation is treated as a regression problem. Crowd attribute recognition is applied on WWW Crowd data-set. The analysis of High Density Crowds in videos describes methods like data driven crowd analysis and density aware tracking. Data driven analysis learn crowd motion pat terns from large collection of crowd videos through an of line manner. Learned pattern can be applied or transferred in applications. The solution includes a two step procedure. Global crowded scene matching and local crowd patch matching. The database selected for experimental evaluation includes 520 unique videos with 720×480 resolutions. The main evaluation is to track unusual and unexpected actions of individuals in a crowd. Through experiments it is proven that data driven tracking is better than batch mode tracking. Density based person detection and tracking include steps like baseline detector, geometric filtering and tracking using density aware detector. A review on classifying abnormal behavior in crowd scene mainly demonstrates four key approaches such as Hidden Markov Model (HMM), GMM, optical flow and STT. GMM itself is enhanced with different techniques to capture abnormal behaviour.

The enhanced versions of GMM are:-

- GMM
- GMM and Markov random field
- Gaussian Poisson mixture model and
- GMM and support vector machine

GMM architecture includes components like local descriptor, global descriptor, classifiers and finally a fusion strategy. The distinction between normal and abnormal behaviour is evaluated based on Mahalanobis distance method. GMM–MRF model mainly divided into two sections where first section identifies motion pattern through GMM and crowd context modelling is done through MRF. GPMM adds one extra feature such as count of occurrence of observed behaviour. Also, EM is used for training at later stage of GPMM. GMM–SVM incorporate features such as crowd collectives, crowd density, crowd conflict etc. for abnormality detection.

HMM has also variants like -

- GM-HMM
- SLT-HMM
- MOHMM
- HM and OSVMs

Hidden Markov Model is a density aware detection method used to detect motion based abnormality. The method generates foreground mask and perspective mask through ORB detector. GM-HMM involves four major steps. First step GMM is used for identifying foreground pixels and further lead to development of blobs generation. In second stage PCA–HOG and motion HOG are used for feature extraction. The third stage applies k means clustering to separately cluster features generated through PCA–HOG and motion–HOG. In final stage, HMM processes continuous information of moving target through the application of GM. In SLT-HMM short local trajectories are used along with HMM to achieve better localization of moving objects. MOHMM uses KLT in first phase to generate trajectories and clustering is applied on them. Second phase uses MOHMM to represent the trajectories to define usual and unusual frames. OSVM uses kernel functions to solve the nonlinearity problem by mapping high dimensional features in to a linear space by using kernel function. In optical flow based method the enhancements made are categorized into following techniques such as HOFH, HOFME, HMOFP and MOFE. In HOFH video frames are divided into several same size patches. Ten optical flows are extracted. It is divided into eight directions. Ten expectation and variance features are used to calculate optical flow between frames. HOFME descriptor is used at the final stage of abnormal behaviour detection.

As the first step frame difference is calculated then extraction of optical flow pattern and finally spatial-temporal description using HOFME is completed. HMOFP Extract optical flow from each frame and divided into patches. The optical flows are segmented into number of bins. Maximum amplitude flows are concatenated to form global HMOFP. MOFE method convert frames into blobs and optical flow in all the blobs are extracted. These optical flows are then clustered into different groups. In STT, crowd tracking and abnormal behaviour detection is done through combing spatial and temporal dimensions of features. Crowd behaviour analysis from fixed and moving cameras covers topics like microscopic and macroscopic crowd modeling, crowd behavior and crowd density analysis and datasets for crowd behavior analysis. Large crowds are handled through macroscopic approaches. Here agents are handled as a whole. In microscopic approaches agents are handled individually. Motion information to represent crowd can be collected through fixed and moving cameras. CNN based methods like end to end deep CNN, Hydra-CNN architecture, switching CNN, cascade CNN architecture, 3D CNN and spatial-temporal CNN are discussed for crowd behaviour analysis. The metrics used are MOTA (multiple person tracker accuracy) and MOTP (multiple person tracker precision). These metrics consider multi target scenarios usually present in crowd scenes. The data-set used for experimental evaluation consists of UCSD, Violent-flows, CUHK, UCF50, Rodriguez's, the mall and finally the world Expo's data-set. Zero-shot crowd behavior recognition suggests recognizer with no or little training data. The basic idea behind the approach is attribute-context co-occurrence. Prediction of behavioral attribute is done based on their relationship with known attributes. The method encompasses different steps like probabilistic zero

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shot prediction. The method calculates the conditional probability of known to original appropriate attribute relation. The second step includes learning attribute relatedness from Text Corpora and Context learning from visual co-occurrence. Computer vision based crowd disaster avoidance system: a survey covers different perspectives of crowd scene analysis such as number of cameras employed and target of interest. Along with that crowd behavior analysis, people count, crowd density estimation, person re identification, crowd evacuation, and forensic analysis on crowd disaster and computations on crowd analysis. A brief summary about bench-marked datasets are also given. Fast Face Detection in Violent Video Scenes suggests an architecture with three steps such as violent scene detector, a normalization algorithm and finally a face detector.

Rejecting Motion Outliers for Efficient Crowd Anomaly Detection provides a solution which consists of two phases. Feature extraction and anomaly classification. Feature extraction is based on flow. Different steps involved in the pipeline are input video is divided into frames, frames are divided into super pixels, extracting histogram for each super pixel, aggregating histograms spatially and finally concatenation of combined histograms from consecutive frames for taking out final feature. Anomaly can be detected through existing classification algorithms. The implementation is done through UCSD data-set. Two subsets with resolution  $158 \times 238$  and  $240 \times 360$  are present. The normal behavior was used to train k means and KUGDA. The normal and abnormal behavior is used to train linear SVM. The hardware part includes Artix 7 xc7a200t FPGA from Xilinx, Xilinx IST and XPower Analyzer. Deep Metric Learning for Crowdedness Regression [84] includes deep network model where learning of features and distance measurements are done concurrently. Metric learning is used to study a fine distance measurement. The proposed model is implemented through Tensorflow package. Rectified linear unit is used as an activation function. The training method applied is gradient descent. Performance is evaluated through mean squared error and mean absolute error. The World-expo data-set and the Shanghai Tech data-set are used for experimental evaluation. A Deep Spatial Temporal Perspective for Understanding Crowd Behavior is a combination of convolution layer and long short-term memory. Spatial information's are captured through convolution layer and temporal motion dynamics are confined through LSTM. The method forecasts the pedestrian path, estimate the destination and finally categorize the behavior of individuals according to motion pattern. Path forecasting technique includes two stacked ConvLSTM layers by 128 hidden states. Kernel of ConvLSTM size is  $3 \times 3$ , with a stride of 1 and zero-padding. Model takes up a single convolution layer with a  $1 \times 1$  kernel size. Crowd behavior classification is achieved through a combination of three layers namely an average spatial pooling layer, a fully connected layer and a soft max layer. Crowded Scene Understanding by Deeply Learned Volumetric Slices suggests a deep model and different fusion approaches.

The architecture involves convolution layers, global sum pooling layer and fully connected layers. Slice fusion and weight sharing schemes are required by the architecture. A new concept of crowd motion channels are designed as input to the model. The motion channel analyzes the temporal progress of contents in crowd videos. The motion channels are stirred by temporal slices that clearly demonstrate the temporal growth of contents in crowd videos. In addition, we also conduct wide-ranging evaluations by multiple deep structures with various data fusion and weights sharing schemes to find out temporal features. The network is configured with convolution layer, pooling layer and fully connected layer with activation functions such as rectified linear unit and sigmoid function. Three different kinds of slice fusion techniques are applied to measure the efficiency of proposed input channels. Crowd Scene Understanding from Video A survey mainly deals with crowd counting. Different approaches for crowd counting are categorized into six. Pixel level analysis, texture level analysis, object level analysis, line counting, density mapping and joint detection and counting. Edge features are analyzed through pixel level analysis. Image patches are analyzed through texture level analysis. Object level analysis is more accurate compared to pixel and texture analysis. The method identifies individual subjects in a scene. Line counting is used to take the count of people crossed a particular line.

As an analysis of existing methods, the following shortcomings were identified. Real world problems are having following objectives like:-

- Time complexity
- Bad weather conditions
- Real world dynamics
- Occlusions
- Overlapping of objects

Existing methods were handling the problems separately. No method handles all the objectives as features in a single proposal. To handle effective intelligent crowd video analysis in real time the method should be able to provide solutions to all these problems. Traditional methods are not able to generate efficient economic solution in a time bounded manner. The availability of high performance computational resource like GPU allows implementation of deep learning based solutions for fast processing of big data. Existing deep learning architectures or models can be combined by including good features and removing unwanted features.

### 3. Conclusion

The paper reviews intelligent surveillance video analysis techniques. Reviewed papers cover wide variety of applications. The techniques, tools and data-set identified were listed in form of tables. Survey begins with video surveillance analysis in general perspective, and then finally moves towards crowd analysis. Crowd analysis is difficult in such a way that crowd size is large and dynamic in real world scenarios. Identifying each entity and their behavior is a difficult task. Methods analyzing crowd behavior

were discussed. The issues identified in existing methods were listed as future directions to provide efficient solution [1-110].

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