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PERFORMANCE EVALUTION OF VIDEO SURVEILLANCE USING METE, MELT AND NIDC TECHNIQUE

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Abstract- To evaluate multi-target video tracking results, one needs to quantify the accuracy of the estimated target-size and the Cardinality error as the well as measure the frequency of occurrence of ID changes. By surveying existing multi-target tracking performance scores and, after discussing their limitations, the work proposes three parameter-independent measures for evaluating multi target video tracking. The measures consider target-size variations, combine accuracy and cardinality errors, quantify long-term tracking accuracy at different accuracy levels, and evaluate ID changes relative to the duration of the track in which they occur. The work conduct an extensive experimental validation of the proposed measures by comparing them with existing ones and by evaluating four state-of-the-art trackers on challenging real world Publicly-available data sets. The software implementing the proposed measures is made available online to facilitate their use by the research community.

Index terms*: *Multi-TargetTrack-Before-Detect(MT-TBD),Single Particle Tracking (SPT),Multiple Extended Target Lost Track Ratio(MELT).

I. INTRODUCTION

The term digital image refers to processing of a two dimensional picture by a digital computer. In a broader context, it implies digital processing of any two dimensional data. A digital image is an array of real or complex numbers represented by a finite number of bits. An image given in the form of a transparency, slide, photograph or an X-ray is first digitized and stored as a matrix of binary digits in computer memory. This digitized image can then be processed and/or displayed on a high-resolution television monitor. For display, the image is stored in a rapid-access buffer memory, which refreshes the monitor at a rate of 25 frames per second to produce a visually continuous display .Digital image processing refers processing of the image in digital form. Modern cameras may directly take the image in digital form but generally images are originated in optical form. They are captured by video cameras and digitalized. The digitalization process includes sampling, quantization. Then these images are processed by the five fundamental processes, at least any one of them, not necessarily all of them. Image enhancement operations improve the qualities of an image like improving the image's contrast and brightness characteristics, reducing its noise content, or sharpen the details. This just enhances the image and reveals the same information in more understandable image. It does not add any information to it. Image restoration like enhancement improves the qualities of image but all the operations are mainly based on known, measured, or degradations of the original image. Image restorations are used to restore images with problems such as geometric distortion, improper focus, repetitive noise, and camera motion. It is used to correct images for known degradations .Image analysis operations produce numerical or graphical information based on characteristics of the original image. They break into objects and then classify them. They depend on the image statistics. Common operations are extraction and description of scene and image features, automated measurements, and object classification. Image analyze are mainly used in machine vision applications. Image compression and decompression reduce the data content necessary to describe the image. Most of the images contain lot of redundant information, compression removes all the redundancies. Because of the compression the size is reduced, so efficiently stored or transported. The compressed image is decompressed when displayed. Lossless compression preserves the exact data in the original image, but Loss compression does not represent the original image but provide excellent compression. Image synthesis operations create images from other images or non-image data. Image synthesis operations generally create images that are either physically impossible or impractical to acquire. To compare the proposed evaluation techniques to existing techniques. Tracking Measurement is considering the accuracy, cardinality error, Id changes. In those specifications are important for best tracking analyzer. The work proposes a novel adaptive empirical standalone method for track-quality estimation that is applicable to image sequences with multiple tracking errors and recoveries. The proposed framework is based on a two-stage adaptive strategy that first determines when a target is being successfully tracked (temporal segmentation) and then estimates track quality during successful tracking. The framework effectively combines the filter uncertainty and the time-reversibility constraint of a tracker to measure the quality of the estimated target state. The analysis of the filter uncertainty allows one detecting unstable tracking results and the detection of a recovery after a tracking failure by applying a reverse tracker. The work demonstrate the proposed approach in a particle filter framework over a heterogeneous dataset with sequences containing tracking challenges such as occlusions, clutter and appearance changes.

II. Literature survey

The absence of a commonly adopted performance evaluation framework is hampering advances in the design of effective video trackers. In this paper, the work presents a single score evaluation measure and a protocol to objectively compare trackers. The proposed measure evaluates tracking accuracy and failure, and combines them for both summative and formative performance assessment. The proposed protocol is composed of a set of trials that evaluate the robustness of trackers on a range of test scenarios representing several real-world conditions [1].

Author[2] proposes a generic online Multi-Target Track-Before-Detect (MT-TBD) that is applicable on confidence maps used as observations. The proposed tracker is based on particle filtering and automatically initializes tracks. The main novelty is the inclusion of the target ID into the particle state, enabling the algorithm to deal with unknown and large number of targets. To overcome the problem of mixing IDs of targets close to each other, the work propose a probabilistic model of target birth and death based on a Markov Random Field (MRF) applied to the particle IDs. Each particle ID is managed using the information carried by neighbouring particles. The assignment of the IDs to the targets is performed using Mean-Shift clustering and supported by a Gaussian Mixture Model. the work also show that the computational complexity of MT-TBD is proportional only to the number of particles.

The work proposes an adaptive framework to estimate the quality of video tracking algorithms without ground-truth data. The framework is divided into two main stages, namely the estimation of the tracker condition to identify temporal segments during which a target is lost and the measurement of the quality of the estimated track when the tracker is successful. The proposed approach is demonstrated on a particle filter tracker over a heterogeneous dataset. Experimental results show the effectiveness and robustness of the proposed framework that improves state-of-art approaches in the presence of tracking challenges such as occlusions, illumination changes and clutter, and on sequences containing multiple tracking errors and recoveries [3].
This work [5] presents a method for evaluating multiple feature spaces while tracking, and for adjusting the set of features used to improve tracking performance. Our hypothesis is that the features that best discriminate between object and background are also best for tracking the object. The work develop an on-line feature ranking mechanism based on the two-class variance ratio measure, applied to log likelihood values computed from empirical distributions of object and background pixels with respect to a given feature. This feature ranking mechanism is embedded in a tracking system that adaptively selects the top-ranked discriminative features for tracking .Author [6]present a multi-target tracking system that is designed specifically for the provision of stable and accurate head location estimates. By performing data association over a sliding window of frames, to correct many data association errors and fill in gaps where observations are missed. The work [7] analyze the computational problem of multi-object tracking in video sequences. Author formulate the problem using a cost function that requires estimating the number of tracks, as well as their birth and death states. Greedy algorithms allow one to embed pre-processing steps, such as non max suppression, within the tracking algorithm. Furthermore, the work give a near-optimal algorithm based on dynamic programming which runs in time linear in the number of objects and linear in the sequence length. Our algorithms are fast, simple, and scalable, allowing us to process dense input data. This results in state-of-the-art performance.
We [8] model each sub-interaction by a dynamic probabilistic model and propose a modified factorial hidden Markov model (HMM) with factored observations. The complete interaction is represented with a network of dynamic probabilistic models (DPMs) by an ordered concatenation of sub-interaction models. The rationale for this approach is that it is more effective in utilizing common components, i.e., sub-interaction models, to describe complex interaction patterns. By

assembling these sub-interaction models in a network, possibly with a mixture of different types of DPMs, such as standard HMMs, variants of HMMs, dynamic Bayesian networks, and so on, we can design a robust model for the analysis of human interactions. We show the feasibility and effectiveness of the proposed method by analyzing the structure of network of DPMs and its success on four different databases: a self-collected dataset, Tsinghai University's dataset, the public domain CAVIAR dataset, and the Edinburgh Informatics Forum Pedestrian dataset. The work [9] propose an efficient L1 tracker with minimum error bound and occlusion detection which we call Bounded Particle Re sampling (BPR)-L1 tracker. First, the minimum error bound is quickly calculated from a linear least squares equation, and serves as a guide for particle re sampling in a particle filter framework. Without loss of precision during re sampling, most insignificant samples are removed before solving the computationally expensive `1 minimization function. The BPR technique enables us to speed up the L1 tracker without sacrificing accuracy. Second, we perform occlusion detection by investigating the trivial coefficients in the `1 minimization. In this Work, Author[10] describes address the problem of automatically detecting and tracking a variable number of persons in complex scenes using a monocular, potentially moving, uncalibrated camera. The work proposes a novel approach for multi-person tracking-by detection in a particle filtering framework. In addition to final high-confidence detections, our algorithm uses the continuous confidence of pedestrian detectors and online trained, instance-specific classifiers as a graded observation model. Thus, generic object category knowledge is complemented by instance-specific information. The main contribution of this paper is to explore how these unreliable information sources can be used for robust multi-person tracking. The algorithm detects and tracks a large number of dynamically moving persons in complex scenes with occlusions, does not rely on background modeling, requires no camera or ground plane calibration, and only makes use of information from the past.

III. Proposed system

Performance evaluation of image surveillance systems is an essential requirement, particularly when the system is deployed in a live environment. Our motivation for the work presented in this paper is to resolve some of the issues that arise when evaluating the performance of a video tracking algorithm. Video tracking is a widely researched topic with applications in event detection, surveillance and behavior analysis. These applications may involve simultaneous tracking of multiple moving targets using a point-target representation (e.g. feature-point tracking) or an extended-target representation (e.g. in face or person tracking). Point target representations use target position information, whereas extended-target representations also include information about the region covered by the target in the image plane. A tracking error is generally quantified by computing the discrepancy between estimated and ground-truth target regions. Ground-truth-free tracking evaluation frameworks also exist that provide performance assessment by enforcing constraints such as time reversibility and feature consistency of the estimated tracks shown in fig 1

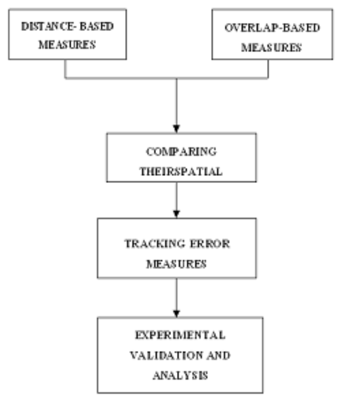


Fig:1 Block diagram of proposed system

3.1 Multiple Extended-Targets Tracking Error

The proposed overlap-based Multiple Extended-target Tracking Error (METE) measure combines accuracy and cardinality errors in a parameter-independent manner. The use of spatial overlap information in METE eliminates the need to include OSPA parameters, namely the penalty for the estimated states located far away from any of the ground truth states and the cut-off parameter defining the upper bound. The accuracy error, *Ak*, represents the extent of the mismatch between estimated and ground-truth states at frame *k* and is defined as

$$\mathcal{A}_k = \min_{\pi \in \Pi_{max(v_k,u_k)}} \sum_{i=1}^{min(v_k,u_k)} \left(1 - O(\bar{A}_{k,i}, A_{k,\pi(i)})\right), \qquad \text{-----} \quad \text{----(1)}$$

The accuracy error is in fact computed for the associated pairs only. This justifies the computation of the cardinality error, *Ck*, namely the discrepancy in estimating the number of targets:

$$\mathcal{C}_k = |u_k - v_k|. \quad \text{------------------(2)}$$

The work combine *Ck* with *Ak* to account for the unassociated targets in the evaluation procedure (in OSPA) and to provide a single-score performance evaluation at frame level. METE is therefore computed as:

$$\mathrm{METE}_k = \frac{\mathcal{A}_k + \mathcal{C}_k}{max(v_k, u_k)}, \quad \text{----------(3)}$$

3.2 Multiple Extended-Target Lost-Tracks Ratio

The proposed Multiple Extended-target Lost-Track ratio (MELT) evaluates tracking accuracy across the sequence in a parameter-independent manner and enables analysis at different levels of accuracy. Given $\overline{X}$ and *X*, the association is first performed at each frame based on the minimization of the cost *(*1−*O(* • *))* computed for all pairs of 6. estimated and ground truth targets. Similarly to Eq. 19, the minimization process uses the Hungarian algorithm. The procedure yields a unique assignment at frame level, whereas at track level a ground truth track may be associated with more than one estimated track due to fragmentations and/or ID changes.

The work quantify tracking performance by defining the Multiple Extended-target Lost

$$\mathrm{MELT}_\tau = \frac{1}{V}\sum_{i=1}^{V} \lambda_i^\tau, \quad \text{---(4)}$$

While the computation of MELT τ may be useful from an application viewpoint, the performance comparison among trackers can be facilitated by providing the single-score average tracking performance which is generated as

$$\mathrm{MELT} = \frac{1}{S_\tau}\sum_{\tau \in \mathbb{R}_{(0,1]}} \mathrm{MELT}_\tau. \quad \text{-----------------------(5)}$$

3.3 Normalized ID Changes

The proposed Normalized ID Changes (NIDC) measure evaluates the ID changes taking into account the track duration in which they occur. In the case of a comparison of trackers producing tracks of different lengths, the normalization of ID changes is preferable to simply counting the ID changes. Such quantification emphasizes the long-term tracking ability with unique IDs of trackers. Moreover, since the score is normalized it can be more useful than the number of ID changes to compare trackers across different datasets.

$$\mathrm{NIDC}_i = \frac{|IDC_i|}{\mathrm{IDC}_i^{max}} \qquad \text{--------------------(6)}$$

3.4 Video Tracking

Video tracking is the process of locating a moving object (or multiple objects) over time using a camera. It has a variety of uses, some of which are: human-computer interaction, security and surveillance, video communication and compression, augmented reality, traffic control, medical imaging and video editing. Video tracking can be a time consuming process due to the amount of data that is contained in video. Adding further to the complexity is the possible need to use object recognition techniques for tracking, a challenging problem in its own right .The objective of video tracking is to associate target objects in consecutive video frames. The association can be especially difficult when the objects are moving fast relative to the frame rate. Another situation that increases the complexity of the problem is when the tracked object changes orientation over time. For these situations video tracking systems usually employ a motion model which describes how the image of the target might change for different possible motions of the object.

3.5 Single Target Tracking

Single Particle Tracking (SPT) is the observation of the motion of individual particles within a medium. The coordinates (x, y, z) over a series of time steps is referred to as a trajectory. The trajectory can be analyzed to identify modes of motion or heterogeneities in the motion such as obstacles or regions of fast transport (e.g. due to active transport or flow), in the case of random motion trajectory analysis can provide a diffusion coefficient.(e.g. It’s shown in the Fig 2&3)

Figure 2: Single Target Present in the Image

Fig 3: Single Target Tracking

3.6 Multi-Target Tracking

The first step of processing requires the pedestrians in a scene to be tracked, with the purpose of providing stable head images for the following pose estimation step. The work track only the heads of pedestrians rather than their entire bodies for two reasons. The first is that security cameras are generally positioned sufficiently high to allow pedestrian's faces to be seen, so their heads are rarely obscured. The second is that the offset between the centre of a pedestrian's body and their head changes as they walk, so tracking the head directly provides more accurately positioned head images. The general approach the work take is to combine absolute location estimates from a head detector based on Histograms of Oriented Gradients (HOG) with velocity estimates from feature-based tracking.It used a similar approach to track pedestrians by combining detections with mean-shift tracking to fill in the gaps between detections. Our approach is instead based on a Kalman filter but the work replace the process model, which usually predicts the next state based on physics, with the velocity estimations from feature tracking. Using a Kalman filter allows the two types of measurement to be combined probabilistically and additionally the covariance can be used to limit the region in which the detector needs to be applied. The video sequences that the work used well fully calibrated relative to a known ground plane. Using calibrated videos the locations of people's feet on the ground plane to be estimated from their head locations by assuming an average human height of 1.7 meters.

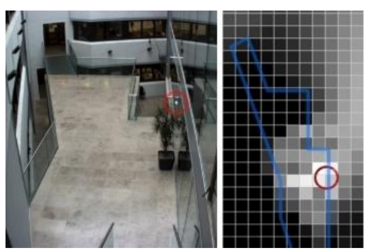


Fig 4 : Multiple Target Present in the Image

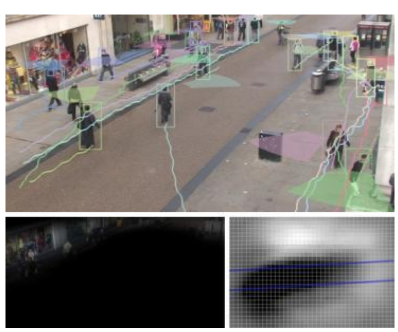


Fig 5 : Multiple Target Tracking

The calibrations also the approximate head size to be calculated to limit the scale range of the HOG detector.(e.g. it's Shown the Fig 4&5)

3.7 Computer Vision

Computer vision is a field that includes methods for acquiring, processing, analyzing, and understanding images and, in general, high-dimensional data from the real world in order to produce numerical or symbolic information, *e.g.*, in the forms of decisions. A theme in the development of this field has been to duplicate the abilities of human vision by electronically perceiving and understanding an image. This image understanding can be seen as the disentangling of symbolic information from image data using models constructed with the aid of geometry, physics, statistics, and learning theory. Computer vision has also been described as the enterprise of automating and integrating a wide range of processes and representations for vision perception.

3.8 Performance evaluation

The work proposed three measures (METE, MELT, NIDC) that quantify key factors in extended multi-target tracking: accuracy, cardinality and ID changes. These measures are parameter independent, numerically bounded and account for target-size changes. METE provides a holistic error assessment using an effective trade-off between accuracy and cardinality errors. (e.g. shown in the Fig 6)

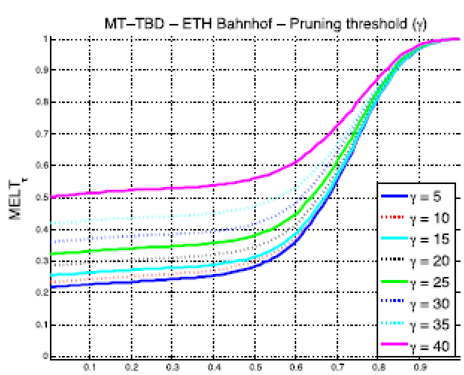


Fig 6: Performance Evaluation of Video Tracking Results

3.9 Background Attention

The pedestrians were tracked in a busy town centre street. Up to thirty pedestrians were tracked simultaneously and had their gaze directions estimated. A gaze map was built up over the full twenty-two minute video sequence, covering approximately 2200 people. When projected, the attention map identifies the shops on the left of the view as a common subject of attention.

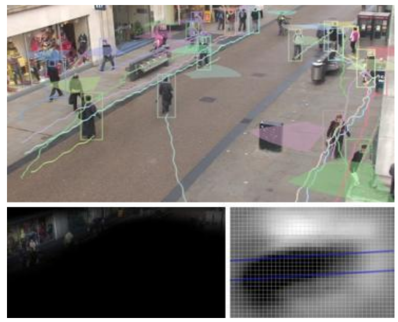


Fig 7: Background Attention

3.10 Artificial Stimulus

The purpose of that concept is an artificially draw the attention of pedestrians to a particular location. To achieve this, a bright light was attached to the wall at the location indicated by the red circle in the above images. The blue lines show the outline of the floor. For this experiment the attention map was generated by taking the difference between the attention received both with and without the light stimulus to correct for the stimuli normally present in the scene. A total of 200 minutes of video were analyzed and 477 people were tracked. (e.g. Shown in the Fig 8)

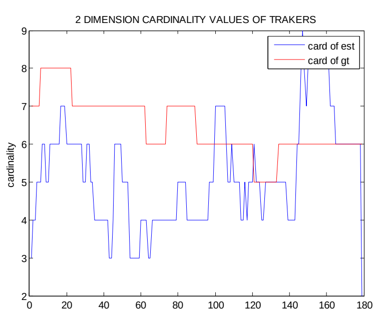


Fig 8: Artificial Stimulus

3.11 Transient Object

The aim of this project is to identify a transient subject of attention. To resolve the ambiguities caused by not knowing the distance between pedestrians and the subject of their attention, the gaze estimates from both people were multiplied and combined over a sliding window of three frames. The resulting intersection correctly identifies the car as the subject of attention when projected back onto the video. (e.g. Shown in the Fig 9)

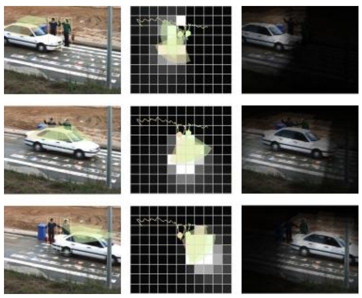


Fig 9: Transient Object

IV. Experimental results

4.1 Evluation 2D -Measure Accuracy and Cardianality Errormete Value

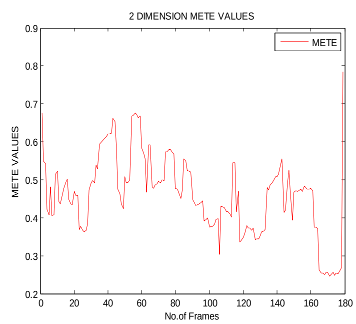


Fig 10: METE Value

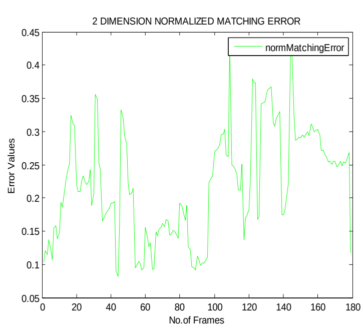


Fig11: Normalized Matching Error

Input is the video tracker datasets, ground truth dataset .Output is the value of multiple extended-target tracking error.METE$k \in [0, 1]$: the lower METEk , the better the tracking result. This is shown in the Fig 10, where METEk = 0 for the best tracking case and METEk = 1 for the worst tracking case.Normalization is Adjustments of values or distributions in statistics.Normalized matching error is obtained by comparing error values with respect to no. of frames as shown in Fig 11.These matching error are made with respect to previous dataset to original one.Input is the video tracker datasets, ground truth dataset.Output is the combination of accuracy error rate and cardinality error rate.The cardinality error is difference between the estimate and ground-truth targets shown in the Fig 12. Fig 13 shows the cardinality of both estimated and ground truth values of trackers.Ground truth is a term used in remote sensing; it refers to information collected on location.Ground truth allows image data to be related to real features and materials on the ground.

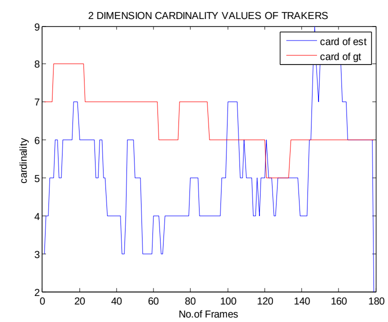


Fig12: Cardinality Error Rate

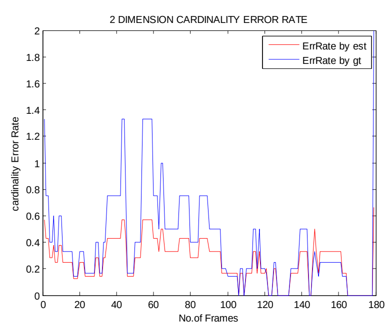


Fig 13: Cardinality Values Of Trackers

42 Measurement of Accuracy and Lost Track Ratio

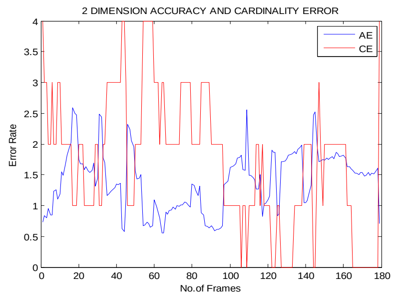


Fig 14: Accuracy and Cardinality Error

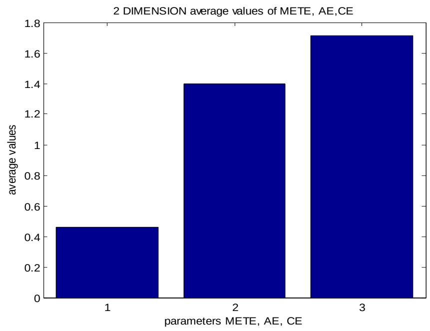


Fig 15: Average Values Of METE, AE, CE

The accuracy error, $A\ k$, represents the extent of the mismatch between estimated and ground-truth states at frame *k.* The cardinality error, *ck*, is difference between the estimate and ground-truth targets. both are shown in the Fig 14.Error rate are obtained with respect to no. of frames .In order to obtain average values of METE, AE, CE the respective parameters are compared with each other .The above Fig 15 shows average values of multiple extended target tracking error, accuracy error and cardinality error

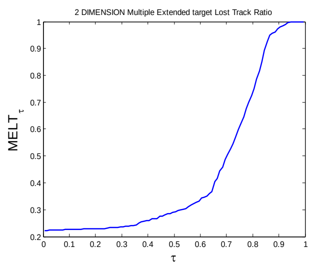


Fig 16: Multiple Extended Target Lost Track Ratio

Input is the Tracker datasets, ground truth dataset .In the output the Accuracy of the dataset and melt values. Multiple Extended-target Lost-Track ratio (MELT) evaluates tracking accuracy across the sequence in a parameter-independent manner and enables analysis at different levels of accuracy as shown in the Fig 16.

15.3 Evaluation 3D Mete Values

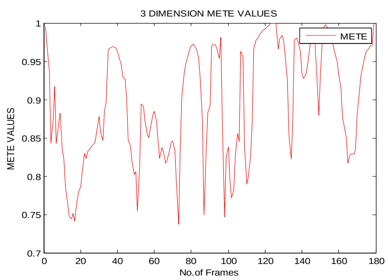


Fig 17: METE Values

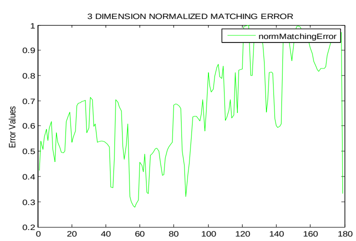


Fig 18: Normalized Matching Error

Input is the video tracker datasets, ground truth dataset In the output value of multiple extended-target tracking error. METE $k \in [0, 1]$: the lower METE k , the better the tracking result. This is shown in the Fig 17, where METE $k = 0$ for the best tracking case and METE $k = 1$ for the worst tracking case. Normalization is Adjustments of values or distributions in statistics. Normalized matching error is obtained by comparing error values with respect to no. of frames as shown in Fig 18.These matching error are made with respect to previous dataset to original one.

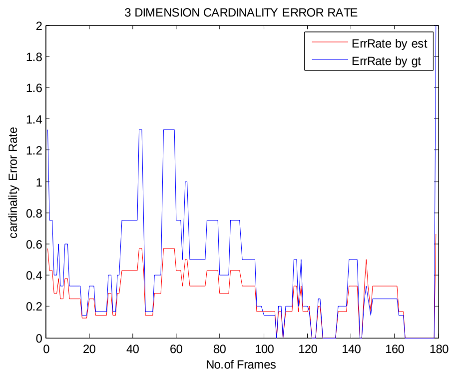
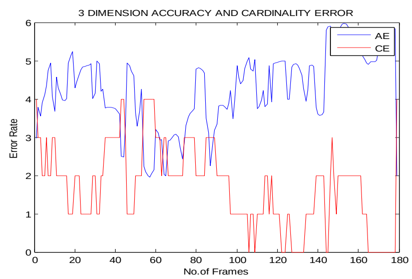


Fig 19: Cardinality Error Rate



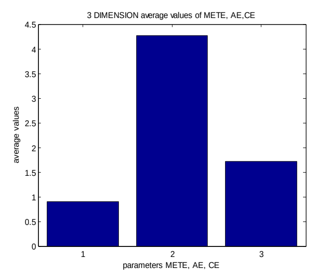


Fig 20: Cardinality Values Of Tracking

Input is the video tracker datasets, ground truth dataset .Output deals thecombination of accuracy error rate and cardinality error rate.The cardinality error is difference between the estimate and ground-truth targets which is shown in the Fig 19.Fig 20 shows the cardinality of both estimated and ground truth values of trackers.Ground truth is a term used in remote sensing; it refers to information collected on location.Ground truth allows image data to be related to real features and materials on the ground

4.3Measurement of Accuracy and Lost Track Ratio

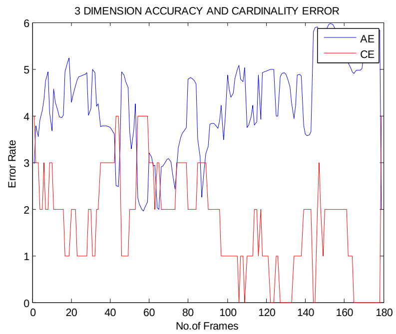


Fig 21: Accuracy and Cardinality Error

The accuracy error, A k , represents the extent of the mismatch between estimated and ground-truth states at frame k. The cardinality error, ck, is difference between the estimate and ground-truth targets. both are shown in the Fig 21.Error rate are obtained with respect to no. of frames. In order to obtain average values of METE, AE, CE the respective parameters are compared with each other. The above Fig 22 shows average values of multiple extended target tracking error, accuracy error and cardinality error. Input is the Tracker datasets, ground truth dataset. Out put deals the Accuracy of the dataset and melt values .Multiple Extended-target Lost-Track ratio (MELT) evaluates tracking accuracy across the sequence in a parameter-independent manner and enables analysis at different levels of accuracy are shown in the Fig 23

Fig 22: Average Values Of METE, AE, CE

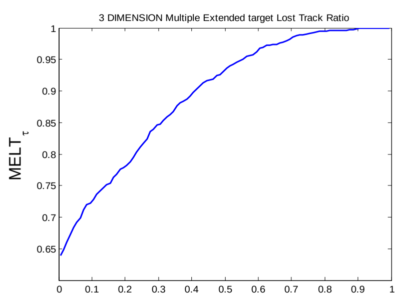


Fig 23: Multiple Extended Target Lost Track Ratio

V. Conclusion

The work proposes three measures such as (METE, MELT, and NIDC) that quantify key factors in extended multi-target tracking: accuracy, cardinality and ID changes. These measures are parameter independent, numerically bounded and account for target-size changes. METE provides a holistic error assessment using an effective trade-off between accuracy and cardinality errors. MELT enables the analysis of tracking performance at varying accuracy levels that can facilitate the selection of trackers for specific applications. NIDC penalizes ID changes as a function of the length of the track in which they occur. The work presented an extensive experimental validation and comparison of these measures with the state-of-the-art measures on recent multi-target trackers using real-world sequences.

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