MTTV
An Interactive Trajectory Visualization and Analysis Tool

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Abstract: We present an interactive visualizer that enables the exploration, measurement, analysis and manipulation of trajectories. Trajectories can be generated either automatically by multi-target tracking algorithms or manually by human annotators. The visualizer helps understanding the behavior of targets, correcting tracking results and quantifying the performance of tracking algorithms. The input video can be overlaid to compare ideal and estimated target locations. The code of the visualizer (C++ with openFrameworks) is open source.

1 INTRODUCTION

Visualization aims at presenting complex data in a comprehensible form and helps users to improve their understanding, refine theories and reveal failures. A plethora of research projects investigate behaviors of moving and potentially interacting objects such as cells (Li et al., 2008), particles (Park et al., 2014), insects (Fasciano et al., 2014) or people (Shitrit et al., 2014) based on video recordings. Recent advances in computer vision have led to the automatic generation of metadata (trajectories) that describe motion patterns (Poiesi and Cavallaro, 2014). The observation of trajectory patterns can benefit behavioral studies (Wong, 2012) of animals (Veeraraghavan et al., 2008; Kimura et al., 2014) and humans (Helbing et al., 2000), and can also be useful to localize errors generated by object trackers.

To understand target interactions (Khan et al., 2005), a user has to observe concurrent trajectories and spatio-temporal relationships between points of interest. Moreover, researchers need to analyze the performance of multi-target tracking algorithms by visualizing and understanding errors in the estimated trajectories. Errors include identity switches (Yin et al., 2007), track fragmentation (Li et al., 2009) or drifts (Ross et al., 2008). Evaluation algorithms assess tracking performance offline (Yin et al., 2007; Li et al., 2009) or online (SanMiguel et al., 2012). Tracking assessment is often limited to the numerical analysis of evaluation scores, such as number of identity switches, number of fragmented tracks or percentage of *mostly* tracked objects (Wu and Nevatia, 2006; Zhang et al., 2015). A visual feedback of this information would support the identification of the causes of errors and complement the information provided by the evaluation scores.

While considerable progress has been made in 3D-particle representations to improve the characterization of high-density biological structures (Beheiry and Dahan, 2013), traffic analysis and maritime navigation (Tominski et al., 2012), as well as the 3D visualization of aircraft trajectories (Hurter et al., 2009), appropriate visualizers for the analysis of multi-target video tracking results are still missing (Hoferlin et al., 2009; Whitehorn et al., 2013). We are interested in visualizing trajectories as 2D target locations (on the image plane) tracked over time. A visualization tool should ease the comparison between trajectories and video in order to allow a user to analyze and compare tracking results.

We present a multi-target trajectory visualization software (MTTV), which enables users to explore, analyze and manipulate object tracks. Figure 1 shows the overall flow diagram of the visualization module. The user can select a point in time to overlay the corresponding video frame onto the corresponding trajectories and then move frames forward and backward to analyze the results (Figure 2). A user can visualize (or discard) individual trajectories or choose a transparency level for simultaneously visualizing (or hiding) multiple targets. This feature is particularly useful during occlusions due to overlapping trajectories (Joshi and Rheingans, 2005). MTTV allows the visualization of tracking errors (e.g. fragmented or inaccurate trajectories) as markers with ar-

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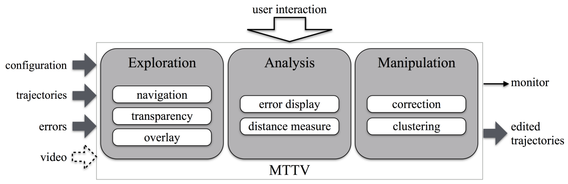


Figure 1: Flow diagram of the multi-target trajectory visualization software (MTTV). Each operation includes different functionalities, for example, trajectories can be analyzed by displaying and correcting errors, and measuring distances among trajectory points. Three files (i.e. configuration, trajectories and errors) plus a video sequence are given as input. MTTV allows correction of errors and the resulting trajectories with new identities can be saved in a file of edited trajectories.

bitrary shape and color. Importantly, the user can manually correct these errors. The corrected trajectory data can then be saved for later visualization and analysis. MTTV is developed in C++ using openFrameworks[1] that eases the interoperability between openGL and openCV. The source code is available at http://www.eecs.qmul.ac.uk/%7Eandrea/mttv.html.

The Graphical User Interface (GUI) of MTTV consists of a window containing the 3D trajectory points (Figure 3a). Each trajectory is represented with a unique color. On the top-left corner of the window there is the list of commands (key-buttons) for enabling/disabling graphical features. In order to have a visualization of the image location of the trajectory points, the current, previous and next frame with respect to that overlaid on the trajectories are shown. The trajectory points at these time instants are overlaid on the frames. The user can explore the trajectories by translating, rotating and zooming to change the viewpoint, focus on specific areas of the scene and observe the trajectory over time. It is also possible to enable transparency, to overlay video frames, to measure distances between points and to reassign identities to trajectories.

2 EXPLORATION

MTTV receives as input a configuration file that contains the list of files to be loaded (i.e. video, trajectory file, error file), the frame range and analysis modality (i.e. *on*/*off*). Each row of the trajectory file is composed of four elements: target identity, horizontal and vertical coordinates, and frame number. The coordinates and frame number are given according to the video format reference. The error file contains the list of errors to be plotted as markers. The error file can

[1] http://openframeworks.cc/, accessed: Dec 2014.

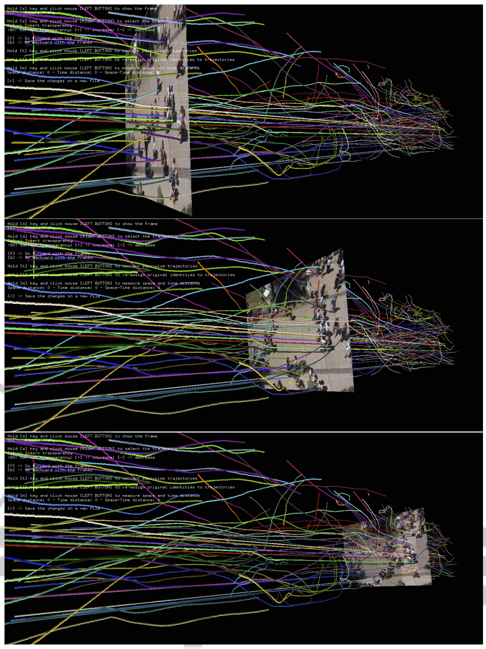


Figure 2: Visualization of 2D trajectories over time with overlaid video frames. Frames can be navigated forward and backward while exploring the 3D space.

be generated by the user using an evaluation software (Nawaz et al., 2014b). The header of this file specifies types and labels of error, colors and types of markers. The list of errors has the same format as the trajectory file.

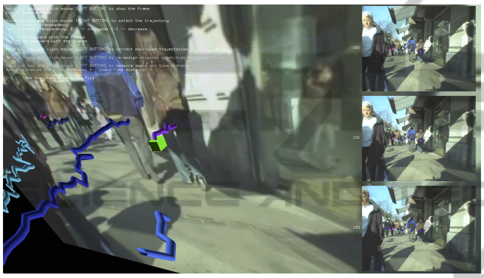
Generally, an observer can only focus his/her attention on five independently moving objects (Pylyshyn, 2003). For this reason, we embedded in MTTV the possibility to set transparencies for the trajectories the user does not want to focus on (Figure 4). This option can be used to present results in reports where only a subset of trajectories of interest are highlighted. In Figure 4b only one trajectory is left with full color (light-blue), thus highlighting the behavior of interest.

3 MANIPULATION

Trajectories can be manipulated by assigning their identities to other trajectories. For example, the identity of a trajectory can be assigned to a group of trajectories if a user aims to generate clusters of trajectories with same identity. MTTV can draw (overlay) the error points that are given as input (Figure 3b - green cube). A user can correct tracking errors by reassigning the identities to the affected trajectories.

MTTV allows the user to transfer the identity of a trajectory to another trajectory. If this process is re-

(a)

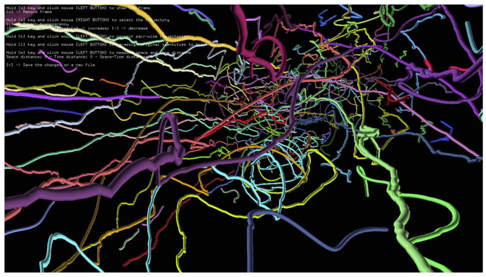


(b)

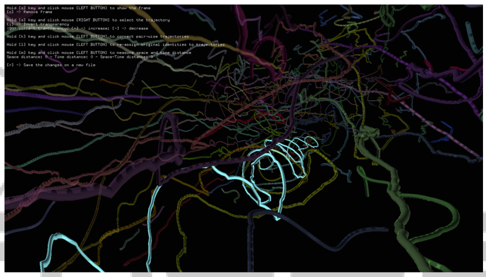
Figure 3: Interface of the visualization software. (a) A user can overlay of a video frame at a certain time instant. The top-left corner contains the legend of the commands (a zoom with the commands is shown on top of the interface). The right-hand side shows current, previous and next frames with respect to that overlaid on the trajectories. (b) Errors can be visualized by enabling the analysis modality.

peated, it is possible to form a cluster (Figure 5 and 6). This type of annotation can be used, for example, to evaluate clustering algorithms (Zhang et al., 2009). Moreover, Figure 5 shows an example of annotation that can be used for the evaluation of methods aimed at detecting groups of people traveling together (Sochman and Hogg, 2011; Solera et al., 2013; Bazzani et al., 2014).

Figure 6a shows an example of a set of trajectories extracted over time and normalized so that they all start at the same time instant (t=0). These trajectories were extracted from a traffic dataset and used to assess the performance of a clustering algorithm (Nawaz et al., 2014a). Trajectories that were given the same identity by a team of annotators were considered belonging to the same cluster. Trajectories that were not associated to any clusters were considered outliers during the annotation process. It is possible to save the results of the manipulated trajectories in a text file (edited trajectories - Figure 1) with the same format as the input trajectory file (Sec. 2).



(a)



(b)

Figure 4: Example of high-density trajectories visualized (a) without and (b) with transparency enabled on a subset of trajectories. The transparency level can be chosen by the user and ranges in the interval [0 255]. (b) The light-blue trajectory is highlighted, whereas the others are set transparent with a transparency value of 80.

4 ANALYSIS

Common errors in multi-target tracking are track fragmentation and identity switches (Wu and Nevatia, 2006; Zhang et al., 2015; Yang and Nevatia, 2014; Milan et al., 2014). A *track fragmentation* occurs when a trajectory is interrupted. An *identity switch* occurs when an estimated trajectory changes its matched ground-truth identity. The analysis of these errors is often carried out by comparing evaluation scores in order to judge the method with best performance (Yang and Nevatia, 2012). However, sometimes errors can be of a different nature and competing methods can be robust to different tracking challenges. MTTV visualizes the spatio-temporal occurrence of errors in order to help the user to identify and assess the causes of the errors, and to show whether the errors of different trackers are of the same type.

MTTV shows the spatio-temporal occurrences of errors using markers when the analysis modality is enabled (Figure 7). The shape and color of markers can be defined in the header of the input error file. The user can input a file with a list of error points to be highlighted on the top of the trajectories in order to associate the errors and the spatio-temporal information of their occurrence. A detailed analysis of the er-

(a)

(b)

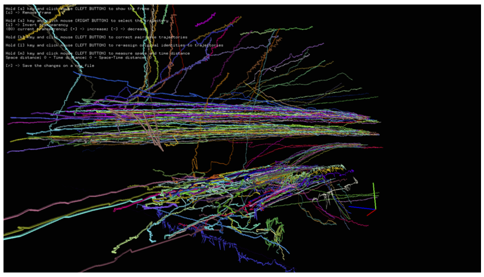
Figure 5: Samples representing (a) trajectories with a different identity (color) associated to each person and (b) clusters of trajectories (with same color) indicating people within the same group.

rors can be further carried out by overlying the video frame in the location of the marker and navigating the video forwards and backwards.

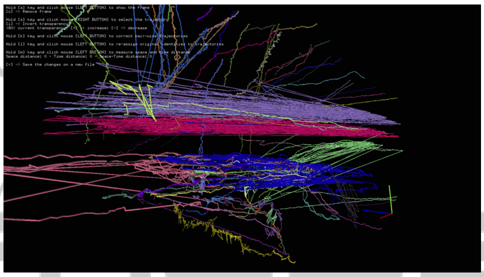
When two events/errors have been localized, it is possible to measure their spatio-temporal distance. Separate measures of time (one dimension) and space (two dimensions) are also provided.

Figure 7 shows an example of tracking result with the green cubes indicating where the estimated tracks have undergone an identity change. In Figure 7a there are three identity changes (green cubes), of which two are due to track fragmentation (center and bottom of the figure) and one is due to identity swap (top of the figure). In Figure 7a the identity change highlighted with the white ellipse is analyzed by superimposing the frames. From Figure 7b we can observe that the target is correctly tracked and after a few frames (Figure 7c) the tracker loses the target, and a new identity is assigned.

When a track fragmentation or identity switch is identified, a user can assign the correct identity to the affected trajectory (Figure 8).



(a)



(b)

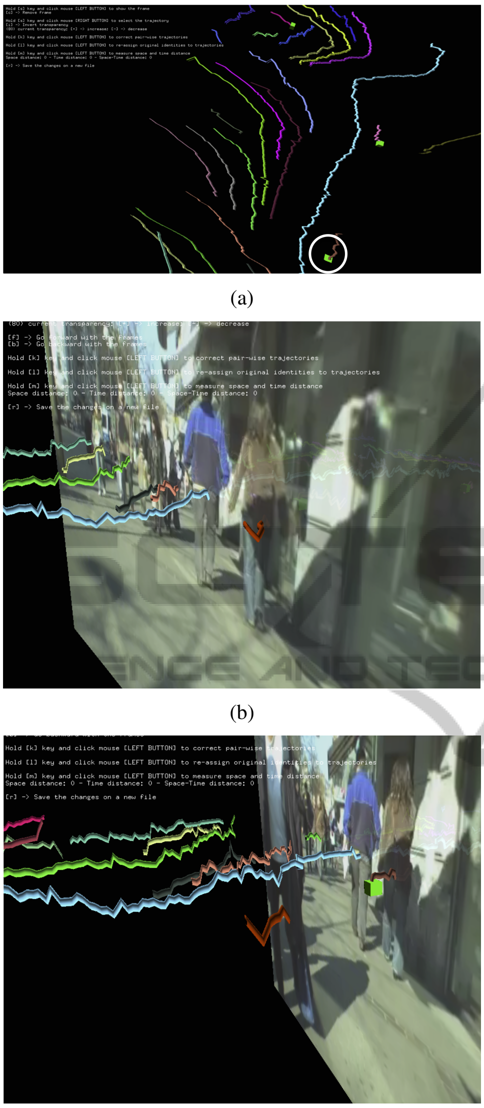
Figure 6: Trajectory clustering (annotation) can be achieved by propagating the identity of a trajectory to the trajectories with same motion patterns. (a) Temporally normalized trajectories that start at same time instant ($t = 0$) and (b) clustered trajectories by annotators.

5 CONCLUSIONS

We presented a new visualization software (MTTV) to measure, understand, analyze and manipulate trajectories. We showed how to navigate the video to assess the results. MTTV can help, for example, the study of isolated target behaviors (e.g. insects (Couvillon et al., 2012)) and the presentation of tracking results or trajectory patterns.

Because the openFrameworks toolkit aims at facilitating interoperability between openGL and openCV, the development of interactive visualization features, for example using Kinect will be made easy. Algorithms for data analysis provided by openCV (e.g. clustering) can be embedded in MTTV and the visualization can be used for a rapid feedback on the results.

One of the limitations of MTTV is the absence of the velocity direction information as proposed by (Buschmann et al., 2014). The implementation of this visualization feature is part of our future work. Moreover, by making the code available open source, we hope that researchers will benefit from this visualizer and contribute to its further development.



(a) (b) (c)

Figure 7: Tracking errors can be plotted in the 3D space and analyzed by superimposing the video frame. (a) Errors (e.g. identity changes) are plotted using green cubes. The white ellipse highlights an example of track fragmentation that is analyzed by (b) superimposing and (c) navigating through the video. (b) The target is correctly tracked and (c) after being lost it is reinitialized with a new identity. This reinitialization leads to an identity change shown with the green cube.

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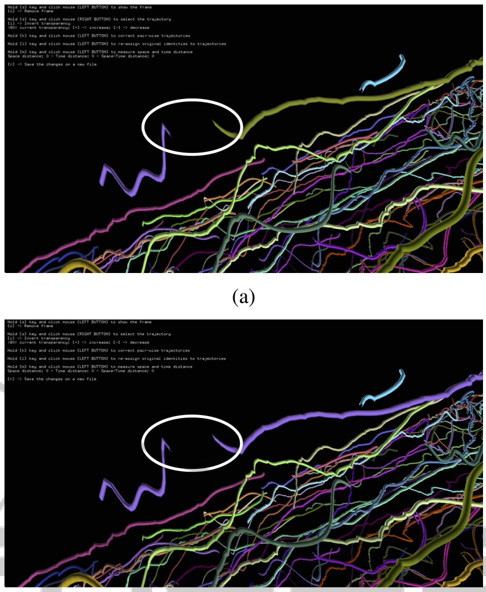

(a) (b)

Figure 8: Fragmented trajectories can be corrected by transferring the identity (same color) of one trajectory to another. (a) The target estimated with the purple trajectory was lost and reinitialized with the green trajectory. This is because the target went outside the scene and when it re-entered the tracker assigned a new identity to it. (b) The purple identity is transferred to the trajectory that initially had green identity.

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