EgoSampling: Wide View Hyperlapse from Single and Multiple Egocentric Videos

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Abstract—The possibility of sharing one's point of view makes use of wearable cameras compelling. These videos are often long, boring and coupled with extreme shake as the camera is worn on a moving person. Fast forwarding (i.e. frame sampling) is a natural choice for faster video browsing. However, this accentuates the shake caused by natural head motion in an egocentric video, making the fast forwarded video useless. We propose EgoSampling, an adaptive frame sampling that gives more stable, fast forwarded, hyperlapse videos. Adaptive frame sampling is formulated as energy minimization, whose optimal solution can be found in polynomial time. We further turn the camera shake from a drawback into a feature, enabling the increase of the field-of-view. This is obtained when each output frame is mosaiced from several input frames. Stitching multiple frames also enables the generation of a single hyperlapse video from multiple egocentric videos, allowing even faster video consumption.

1 INTRODUCTION

While the use of egocentric cameras is on the rise, watching raw egocentric videos is awkward. These videos, captured in an 'always-on' mode, tend to be long and boring. Video summarization [1], [2], [3], temporal segmentation [4], [5] and action recognition [6], [7] methods can help consume and navigate through large amounts of egocentric video. However, these algorithms must make strong assumptions in order to work properly (e.g. faces are more important than unidentified blurred images). The information produced by these algorithms helps the user skip most of the input video. Yet, the only way to watch a video from start to end, faster and without making strong assumptions, is to play it in a fast-forward manner. However, the natural camera shake gets amplified in fast-forward playing (i.e. frame sampling). An exceptional tool for generating stable fast forward video is the recently proposed "Hyperlapse" method [8]. While our work was inspired by [8], we take a different, lighter, approach to address this problem.

Fast forward is a natural choice for faster browsing of egocentric videos. The speed factor depends on the cognitive load a user is interested in taking. Naïve fast forward uses uniform sampling of frames, and the sampling density depends on the desired speed up factor. Adaptive fast forward approaches [9] try to adjust the speed in different segments of the input video so as to equalize the cognitive load. For example, sparser frame sampling giving higher speed up is possible in stationary scenes, and denser frame sampling giving lower speed ups is possible in dynamic scenes. In general, content aware techniques adjust the frame sampling rate based upon the importance of the content in the video. Typical importance measures include scene motion, scene complexity, and saliency. None of the aforementioned methods, however, can handle the challenges of egocentric videos, as we describe next.

Most egocentric videos suffer from substantial camera



Fig. 1. Frame sampling for Fast Forward. A view from above on the camera path (the line) and the viewing directions of the frames (the arrows) as the camera wearer walks forward during a couple of seconds. (a) Uniform $5 \times$ frames sampling, shown with solid arrows, gives output with significant changes in viewing directions. (b) Our frame sampling, represented as solid arrows, prefers forward looking frames at the cost of somewhat non uniform sampling.

shake due to head motion of the wearer. We borrow the terminology of [4] and note that when the camera wearer is "stationary" (e.g, sitting or standing in place), head motions are less frequent and pose no challenge to traditional fastforward and stabilization techniques. However, when the camera wearer is "in transit" (e.g, walking, cycling, driving, etc), existing fast forward techniques end up accentuating the shake in the video. We, therefore, focus on handling these cases, leaving the simpler cases of a stationary camera wearer for standard methods. We use the method of [4] to identify with high probability portions of the video in which the camera wearer is not "stationary", and operate only on these. Other methods, such as [1], [6] can also be used to identify a stationary camera wearer.

Several methods were recently proposed to generate stabilized fast forward videos from shaky egocentric videos [8], [10], [11]. in [8] it was proposed to generate hyperlapse egocentric videos by 3D reconstruction of the input camera

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Fig. 2. An output frame produced by the proposed Panoramic Hyperlapse. We collect frames looking into different directions from the video and create mosaics around each frame in the video. These mosaics are then sampled to meet playback speed and video stabilization requirements. Apart from fast forwarded and stabilized, the resulting video now also has wide field of view. The white lines mark the different original frames. The proposed scheme turns the problem of camera shake present in egocentric videos into a feature, as the shake helps increasing the field of view.

path. A smoother camera path is calculated, and new frames are rendered for this new path using the frames of the original video. Generated video is very impressive, but it may take hours to generate minutes of hyperlapse video. More recent papers [10], [11] suggested to avoid 3D reconstruction by smart sampling of the input frames. Frame selection is biased in favor of forward looking frames, and frames that might introduce shake are dropped.

We propose to model frame sampling as an energy minimization problem. A video is represented as a directed acyclic graph whose nodes correspond to input video frames. The weight of an edge between nodes, e.g. between frame tand frame t + k, represents a cost for the transition from t to t + k. For fast forward, the cost represents how "stable" the output video will be if frame t is followed by frame t + kin the output video. This can also be viewed as introducing a bias, favoring a smoother camera path. The weight additionally indicates how suitable k is to the desired playback speed. In this formulation, the problem of generating a stable fast forwarded video becomes equivalent to that of finding a shortest path in a graph. We keep all edge weights non-negative and note that there are numerous, polynomial time, optimal inference algorithms available for finding a shortest path in such graphs. The proposed frame sampling approach, which we call EgoSampling, was initially introduced in [11]. We show that sequences produced with EgoSampling are more stable and easier to watch compared to traditional fast forward methods.

Frame sampling approach like EgoSampling described above, as well as the ones mentioned in [8], [10], drop frames to give stabilized video. Dropped frames may view valuable information. In addition, a stabilization post process is commonly applied to the subset of selected frames, a process which further reduces the field of view. We propose an extension of EgoSampling, in which instead of dropping unselected frames, these frames are used to increase the field of view of the output video. We call the proposed approach Panoramic Hyperlapse. Fig. 2 shows a frame from an output Panoramic Hyperlapse generated with our method. Panoramic Hyperlapse video is easier to comprehend than [10] because of its increased field of view. Panoramic Hyperlapse can also be extended to handle multiple egocentric videos, such as recorded by a groups of people walking together. Given a set of egocentric videos captured at the same scene, Panoramic Hyperlapse collects content from various such videos into its panoramic frames, generating a stabilized panoramic video for the whole set. The combination of multiple videos into a Panoramic Hyperlapse increases the browsing efficiency.

The contributions of this work are as follows: i) We propose a new method to consume a video of an egocentric camera. The generated wide field-of-view, stabilized, fast forward output videos are easier to comprehend than only stabilized or only fast forward videos. ii) We extend the technique to consume multiple egocentric video streams by collecting frames from such input streams taken by the same or different camera, and create a video having larger field of view, allowing users to watch more egocentric videos in less time.

The original Hyperlapse paper [8] and our EgoSamplingpaper [11] have appeared Earlier. The paper [10] also uses light weight frame sampling strategy as prescribed by us in [11]. In the present work, we extend our EgoSampling strategy to Panoramic Hyperlapse, allowing wide field of view hyperlapse. Extension of our approach to multiple input video scenario is also a novelty of the present work.

The rest of the paper is organized as follows. Relevant related work in described in Section 2. The EgoSampling framework is briefly described in in Section 3. In Section 4 we formulate the sampling framework, and in Sections 5 and 6 we introduce the generalized Panoramic Hyperlapse for single and multiple videos, respectively. We report our experiments in Section 7, and conclude in Section 8.

2 RELATED WORK

The related work to this paper can be broadly categorized into four categories.

2.1 Video Summarization

Video Summarization methods scan the input video for salient events, and create from these events a concise output that captures the essence of the input video. This field has many new publications, but only a handful address the specific challenges of summarizing egocentric videos. In [2], [13], important keyframes are sampled from the input video to create a story-board summarization. In [1], subshots that are related to the same "story" are sampled to produce a "story-driven" summary. Such video summarization can be seen as an extreme adaptive fast forward, where some parts are completely removed while other parts are played at original speed. These techniques require a strategy for determining the importance or relevance of each video segment, as segments removed from summary are not available for browsing. As long as automatic methods are not endowed with human intelligence,



Fig. 3. Representative frames from the fast forward results on 'Bike2' sequence [12]. The camera wearer rides a bike and prepares to cross the road. Top row: uniform sampling of the input sequence leads to a very shaky output as the camera wearer turns his head sharply to the left and right before crossing the road. Bottom row: EgoSampling prefers forward looking frames and therefore samples the frames non-uniformly so as to remove the sharp head motions. The stabilization can be visually compared by focusing on the change in position of the building (circled yellow) appearing in the scene. The building does not even show up in two frames of the uniform sampling approach, indicating the extreme shake. Note that the fast forward sequence produced by EgoSampling can be post-processed by traditional video stabilization techniques to further improve the stabilization.

2.2 Video Stabilization

There are two main approaches for video stabilization. One approach uses 3D methods to reconstruct a smooth camera path [14], [15]. Another approach avoids 3D, and uses only 2D motion models followed by non-rigid warps [16], [17], [18], [19], [20]. A naïve fast forward approach would be to apply video stabilization algorithms before or after uniform frame sampling. As noted also by [8], stabilizing egocentric video doesn't produce satisfying results. This can be attributed to the fact that uniform sampling, irrespective of whether done before or after the stabilization, is not able to remove outlier frames, e.g. the frames when the camera wearer looks at their shoe for a second while walking.

An alternative approach that was evaluated in [8], termed "coarse-to-fine stabilization", stabilizes the input video and then prunes frames from the stabilized video a bit. This process is repeated until the desired playback speed is achieved. Being a uniform sampling approach, this method does not avoid outlier frames. In addition, it introduces significant distortion to the output as a result of repeated application of a stabilization algorithm.

EgoSampling differs from traditional fast forward as well as traditional video stabilization. We attempt to adjust frame sampling in order to produce an as-stableas-possible fast forward sequence. Rather than stabilizing outlier frames, we prefer to skip them. While traditional stabilization algorithms must make compromises (in terms of camera motion and crop window) in order to deal with every outlier frame, we have the benefit of choosing which frames to include in the output. Following our frame sampling, traditional video stabilization algorithms [16], [17], [18], [19], [20] can be applied to the output of EgoSampling to further stabilize the results.

Traditional video stabilization methods aim to eliminate camera shake by applying individual transformations and cropping to each input frame, leading to a possibility of important content getting removed to favor stable looking output. In attempt to reduce the cropping size, Matsushita et. al [21] suggest to perform inpainting of the video boundary, based on information from previous and future frames. Even the frame sampling approaches [8], [10] as well as EgoSampling prefers to drop sideways looking frames. We suggest Panoramic Hyperlapse to counter the shortcoming. The technique, while generating stable fast forward videos, also utilizes side-looking frames in order to increase the field of view by creating panoramic output frames, thereby minimizing the loss of content in the output video.

2.3 Hyperlapse

Kopf et al. [8] have suggested a pioneering hyperlapse technique to generate stabilized egocentric videos using a combination of 3D scene reconstruction and image based rendering techniques. A new and smooth camera path is computed for the output video, while remaining close to the input trajectory. The results produced are impressive but may be less practical because of the large computational requirements. In addition, 3D recovery from egocentric video may often fail. A similar paper to our EgoSampling approach, [10] avoids 3D reconstruction by posing hyperlapse as a frame sampling problem, optimizing some objective function. Similar to EgoSampling strategy, the objective is to produce a stable fast forward output video by dropping frames that introduce shake to the output video, while giving the desired playback speed. The formulation produces stabilized fast forward egocentric video at a fraction of the computational cost compared to [8], and can even be performed in real time.

Sampling-based hyperlapse for either EgoSampling proposed by us or by [10], bias the frame selection towards forward looking views. This selection has two effects: (i) The information available in the skipped frames, likely looking sideways, is lost; (ii) The cropping which is part of the subsequent stabilization step, further reduces the field of view. We propose to extend the frame sampling strategy by Panoramic Hyperlapse, using the information in the outlier frames that were discarded by the frame sampling methods.

2.4 Multiple Input Videos

The hyperlapse techniques described earlier address only a single egocentric video. For curating multiple nonegocentric video streams, Jiang and Gu [22] suggested spatial-temporal content-preserving warping for stitching multiple synchronized video streams into a single panoramic video. Hoshen et. al [23] and Arev et. al [24] produce a single output stream from multiple egocentric videos viewing the same scene. This is done by selecting only a single input video, best representing each time period. The criterion for selecting the one video to display is importance, which require strong assumptions of what is interesting and what is not.

Panoramic Hyperlapse, proposed in this paper, supports multiple input videos, and fuses input frames from multiple videos into a single output frame having a wide field of view.

3 MOTION COMPUTATION

Most egocentric cameras are usually worn on the head. While this gives an ideal first person view, it also leads to significant shake of the camera due to the wearer's head motion. Camera Shake is stronger when the person is "in transit" (e.g. walking, cycling, driving, etc.). In spite of the shaky original video, we would prefer for consecutive output frames in the fast forwarded video to have similar viewing directions, almost as if they were captured by a camera moving forward on rails. In this paper we propose a frame sampling technique which selectively picks frames with similar viewing directions, resulting in a stabilized fast forward egocentric video. See Fig. 3 for a schematic example.

3.1 Head Motion Prior

As noted by [2], [4], [6], [25], the camera shake in an egocentric video, measured as optical flow between two consecutive frames, is far from being random. It contains enough information to recognize the camera wearer's activity. Another observation made in [4] is that when "in transit", the mean (over time) of the instantaneous optical flow is always radially away from the Focus of Expansion (FOE). The interpretation is simple: when "in transit", our head might be moving instantaneously in all directions (left/right/up/down), but the physical transition between the different locations is done through the forward looking direction (i.e. we look forward and move forward). This motivates us to use a forward orientation sampling prior. When sampling frames for fast forward, we prefer frames looking to the direction in which the camera is translating.

3.2 Computation of Motion Direction (Epipole)

Given *N* video frames, we would like to find the motion direction (Epipolar point) between all pairs of frames, I_t and I_{t+k} , where $k \in [1, \tau]$, and τ is the maximum allowed frame skip. Under the assumption that the camera is always translating (when the camera wearer is "in transit"), the displacement direction between I_t and I_{t+k} can be estimated from the fundamental matrix $F_{t,t+k}$ [26]. Frame sampling will be biased towards selecting forward looking frames, where



Fig. 4. We formulate the joint fast forward and video stabilization problem as finding a shortest path in a graph constructed as shown. There is a node corresponding to each frame. The edges between a pair of frames (i, j) indicate the penalty for including a frame j immediately after frame i in the output (please refer to the text for details on the edge weights). The edges between the source/sink and the graph nodes allow to skip frames from start and end. The frames corresponding to nodes along the shortest path from the source to the sink are included in the output video.

the epipole is closest to the center of the image. Recent V-SLAM approaches such as [27], [28] provide camera egomotion estimation and localization in real-time. However, these methods failed on our dataset after a few hundreds frames. We decided to stick with robust 2D motion models.

3.3 Estimation of Motion Direction (FOE)

We found that the fundamental matrix computation can fail frequently when k (temporal separation between the frame pair) grows larger. Whenever the fundamental matrix computation breaks, we estimate the direction of motion from the FOE of the optical flow. We do not compute the FOE from the instantaneous flow, but from integrated optical flow as suggested in [4] and computed as follows: (i) We first compute the sparse optical flow between all consecutive frames from frame t to frame t + k. Let the optical flow between frames t and t + 1 be denoted by $g_t(x,y)$. (ii) For each flow location (x,y), we average all optical flow vectors at that location from all consecutive frames. $G(x,y) = \frac{1}{k} \sum_{i=t}^{t+k-1} g_i(x,y)$. The FOE is computed from G according to [29], and is used as an estimate of the direction of motion.

The temporal average of the optical flow gives a more accurate FOE since the direction of translation is relatively constant, but the head rotation goes to all directions, back and forth. Averaging the optical flow will tend to cancel the rotational components, and leave the translational components. In this case the FOE is a good estimate for the direction of motion. For a deeper analysis of temporally integrated optical flow see "Pixel Profiles" in [19].

3.4 Optical Flow Computation

Most available algorithms for dense optical flow failed for our purposes, but the sparse flow proposed in [4] for egocentric videos worked relatively well. The 50 optical flow vectors were robust to compute, while allowing to find the FOE quite accurately.

4 EGOSAMPLING FORMULATION

We model the joint fast forward and stabilization of egocentric video as graph energy minimization.



Fig. 5. Comparative results for fast forward from naïve uniform sampling (first row), EgoSampling using first order formulation (second row) and using second order formulation (third row). Note the stability in the sampled frames as seen from the tower visible far away (circled yellow). The first order formulation leads to a more stable fast forward output compared to naïve uniform sampling. The second order formulation produces even better results in terms of visual stability.

4.1 Graph Representation

The input video is represented as a graph, with a node corresponding to each frame in the video. There are weighted edges between every pair of graph nodes, i and j, with weight proportional to our preference for including frame j right after i in the output video. There are three components in this weight:

- 1) Shakiness Cost $(S_{i,j})$: This term prefers forward looking frames. The cost is proportional to the distance of the computed motion direction (Epipole or FOE) from the center of the image.
- 2) Velocity Cost $(V_{i,j})$: This term controls the playback speed of the output video. The desired speed is given by the desired magnitude of the optical flow, K_{flow} , between two consecutive output frames. This optical flow is estimated as follows: (i) We first compute the sparse optical flow between all consecutive frames from frame i to frame j. Let the optical flow between frames t and t + 1 be $g_t(x, y)$. (ii) For each flow location (x, y), we sum all optical flow vectors at that location from all consecutive frames. $G(x,y) = \sum_{t=i}^{j-1} g_t(x,y)$. (iii) The flow between frames i and j is then estimated as the average magnitude of all the flow vectors G(x, y). The closer the magnitude is to K_{flow} , the lower is the velocity cost.

The velocity term samples more densely periods with fast camera motion compared to periods with slower motion, e.g. it will prefer to skip stationary periods, such as when waiting at a red light. The term additionally brings in the benefit of content aware fast forwarding. When the background is close to the wearer, the scene changes faster compared to when the background is far away. The velocity term reduces the playback speed when the background is close and increases it when the background is far away.

3) Appearance Cost $(C_{i,j})$: This is the Earth Movers Distance (EMD) [30] between the color histograms of frames *i* and *j*. The role of this term is to prevent large visual changes between frames. A quick rotation of the head or dominant moving objects in the scene can confuse the FOE or epipole computation. This term acts as an anchor in such cases, preventing the algorithm from skipping a large number of frames.

The overall weight of the edge between nodes (frames) i and j is given by:

$$\mathcal{W}_{i,j} = \alpha \cdot \mathcal{S}_{i,j} + \beta \cdot V_{i,j} + \gamma \cdot C_{i,j}, \tag{1}$$

where α , β and γ represent the relative importance of various costs in the overall edge weight.

With the problem formulated as above, sampling frames for stable fast forward is done by finding a shortest path in the graph. We add two auxiliary nodes, a *source* and a *sink* in the graph to allow skipping some frames from start or end. We add zero weight edges from start node to first D_{start} frames and from last D_{end} nodes to sink, to allow such skip. We then use Dijkstra's algorithm [31] to compute the shortest path between source and sink. The algorithm does the optimal inference in time polynomial in the number of nodes (frames). Fig. 4 shows a schematic illustration of the proposed formulation.

We note that there are content aware fast forward and other general video summarization techniques which also measure importance of a particular frame being included in the output video, e.g. based upon visible faces or other objects. In our implementation we have not used any bias for choosing a particular frame in the output video based upon such a relevance measure. However, the same could have been included easily. For example, if the penalty of including a frame, *i*, in the output video is δ_i , the weights of all the incoming (or outgoing, but not both) edges to node *i* may be increased by δ_i .

4.2 Second Order Smoothness

The formulation described in the previous section prefers to select forward looking frames, where the epipole is closest to the center of the image. With the proposed formulation, it may so happen that the epipoles of the selected frames are



Fig. 6. The graph formulation, as described in Fig. 4, produces an output which has almost forward looking direction. However, there may still be large changes in the epipole locations between two consecutive frame transitions, causing jitter in the output video. To overcome this we add a second order smoothness term based on triplets of output frames. Now the nodes correspond to pairs of frames, instead of single frames in the first order formulation described earlier. There are edges between frame pairs (i, j) and (k, l), if j = k. The edge reflects the penalty for including frame triplet (i, k, l) in the output. Edges from source and sink to graph nodes (not shown in the figure) are added in the same way as in the first order formulation to allow skipping frames from start and end.

close to the image center but on the opposite sides, leading to a jitter in the output video. In this section we introduce an additional cost element: stability of the location of the epipole. We prefer to sample frames with minimal variation of the epipole location.

To compute this cost, nodes now represent two frames, as can be seen in Fig. 6. The weights on the edges depend on the change in epipole location between one image pair to the successive image pair. Consider three frames I_{t_1} , I_{t_2} and I_{t_3} . Assume the epipole between I_{t_i} and I_{t_j} is at pixel (x_{ij}, y_{ij}) . The second order cost of the triplet (graph edge) $(I_{t_1}, I_{t_2}, I_{t_3})$, is proportional to $||(x_{23} - x_{12}, y_{23} - y_{12})||$. This is the difference between the epipole location computed from frames I_{t_1} and I_{t_2} , and the epipole location computed from frames I_{t_2} and I_{t_3} .

This second order cost is added to the previously computed shakiness cost, which is proportional to the distance from the origin $||(x_{23}, y_{23})||$. The graph with the second order smoothness term has all edge weights non-negative and the running-time to find an optimal solution to shortest path is linear in the number of nodes and edges, i.e. $O(n\tau^2)$. In practice, with $\tau = 100$, the optimal path was found in all examples in less than 30 seconds. Fig. 5 shows results obtained from both first order and second order formulations.

As noted for the first order formulation, we do not use importance measure for a particular frame being added to the output in our implementation. To add such measure, we can use the same method as described in Sec. 4.1.

5 PANORAMIC HYPERLAPSE OF A SINGLE VIDEO

Sampling based hyperlapse techniques (hereinafter referred to as 'sampled hyperlapse'), such as EgoSampling, or as given in [10], drop many frames for output speed and stability requirements. Instead of simply skipping the unselected frames which may contain important events, we suggest "Panoramic Hyperlapse", which uses all the frames in the video for building a panorama around selected frames. There could be several different approaches for creating a Panoramic Hyperlapse, but we found the following steps to give best results:



Fig. 7. Panoramic Hyperlapse creation. At the first step, for each input frame v_i a mosaic M_i is created from frames before and after it. At the second stage, a Panoramic Hyperlapse video P_i is sampled from M_i using sampled hyperlapse methods such as [10] or EgoSampling.

- A panorama is created around each frame in the input video, using frames from its temporal neighborhood. In our experiments we used 50 input frames for each panorama. This corresponds to about two steps when walking.
- 2) A subset of these panoramas is selected using the traditional sampled hyperlapse.

The approach is illustrated in Fig. 7. Panoramic Hyperlapse has the following benefits over sampled hyperlapse:

- 1) Information in the sideways looking frames is included, creating a larger field of view hyperlapse video.
- 2) While the shake in the output video remains the same, the increased field of view reduces the proportion of shake compared to the frame size. This leads to increased perception of stability of Panoramic Hyperlapse compared to sampled hyperlapse.

Generating a panorama for each input frame as suggested above is time consuming, and may also be wasteful as most panoramas will be discarded in the hyperlapse process. In the approach describe in the next section we avoid creating panoramas before they are used, since it is possible to compute the necessary features of the panoramas without generating them.

5.1 Creating Panoramas

Every panorama starts with a central frame, and all other frames are warped towards it. This is a common approach in mosaicing, and can be seen as far back as [32]. It is recommended in [32] that reference view for the panorama should be "the one that is geometrically most central" (p. 73). In order to choose the best central frame, we take a window of ω frames around each input frame and track feature points through this temporal window. The (coarse) displacement of each frame can be determined by the locations of the feature points. Let $f_{i,t}$ be the displacement of feature point $i \in \{1...n\}$ in frame t relative to its location in the first frame of the temporal window. The displacement of frame



Fig. 8. An example for mapping input frames to output panoramas from sequence 'Running'. Rows represent generated panoramas, columns represent input frames. Red panoramas were selected for Panoramic Hyperlapse, and gray panoramas were not used. Central frames are indicated in green.

t relative to the first frame is defined as the mean of the displacements of all its tracked points:

$$\operatorname{pos}_{t} = \frac{1}{n} \sum_{i=1}^{n} f_{i,t} \tag{2}$$

The frame whose displacement is closest to the mean displacement of all frames is selected as the central frame. The central frame selection strategy described above prefers forward looking frames as central frames.

After the central frame is determined, all other frames in the temporal neighborhood are aligned with the central frame using a homography, and are stitched together. In the examples shown in this paper we use the "joiners" method of [33], where central frames are on top and peripheral frames are at the bottom. More sophisticated stitching and blending, e.g. min-cut and Poisson blending, can be used to improve the appearance of the panorama.

5.2 Sampling Panoramas

In the previous section we generated a panorama for each frame. In the second step we need to select a small subset of panoramas for the hyperlapse video. The strategy to select best panoramas is similar to the process described in Section 4, that selected best subset of frames. Following the same terminology, we create a graph where every node corresponds to a generated panorama, which can possibly be used in the Panoramic Hyperlapse. There is an edge corresponding to every possible transition from one panorama to another in the output video. A weight on an edge represents the cost of the transition from panorama p to panorama q, and is defined as:

$$W_{p,q} = \alpha \cdot S_{p,q} + \beta \cdot V_{p,q} + \gamma \cdot FOV_p, \tag{3}$$

where the shakiness $S_{p,q}$ and the velocity $V_{p,q}$ are measured between the central frames of the two panoramas.

The FOV is the size of the panorama, counted as the number of pixels painted by all frames participating in that panorama. We prefer larger panoramas having wider field of view. For efficiency the FOV is calculated without really warping the frames to the canvas, but only by determining which pixels will be covered.

After creating the graph using the edge weights as mentioned above, we run the shortest path algorithm to select



Fig. 9. The same scene as in Fig. 2. The frames were warped to remove lens distortion, but were not cropped. The mosaicing was done on the uncropped frames. Notice the increased in FOV compared to the panorama in 2.

the sampled frames. We favored the shortest path algorithm over dynamic programming of [10], as it allows "branches", eg. when a group of camera wearers splits, the hyperlapse should choose which video to continue with, based on the quality of the produced hyperlapse. We explain more about such cases in the next section.

Fig. 8 shows the participation of input frames in the panoramas for one of the sample sequence. We show in gray the candidate panoramas before sampling, and the finally selected panoramas are shown in red. The span of each row shows the frames participating in each panorama.

5.3 Stabilization

In order to show the strength of the panoramic effect, we performed only minimal alignment between panoramas. We aligned each panorama towards the one before it using only a rigid transformation between the central frames of the panoramas. When feature tracking was lost we placed the next panorama at the center of the canvas and started tracking from that frame.

5.4 Cropping

Panoramas are created on a canvas much larger than the size of the original video, and large parts of the canvas are not covered with any of the input images. We applied a moving crop window on the aligned panoramas. The crop window was reset whenever the stabilization was reset. In order to get smooth window movement, while containing as many pixels as possible we find crop centers cr_i which minimize the following energy function:

$$E = \sum \|cr_i - m_i\|^2 + \lambda \sum \|cr_i - \frac{cr_{i-1} + cr_{i+1}}{2}\|^2, \quad (4)$$

where m_i is the center of mass of the i^{th} panorama. This can be minimized by solving the sparse set of linear equations given by the derivatives:

$$cr_i = \frac{\lambda(cr_{i-1} + cr_{i+1}) + m_i}{2\lambda + 1} \tag{5}$$

5.5 Removing Lens Distortion

Removal of lens distortion for the creation of perspective images is a common pre-processing step when creating

Algorithm 1: Single video Panoramic Hyperlapse
Data: Single video
Result: Panoramic Hyperlapse
for every temporal window do
_ find the central frame of the window;
for every panorama candidate with center c do
for <i>each frame f participating in the panorama</i> do Calculate the transformation between <i>f</i> and <i>c</i> ; Calculate the cost for shakiness, FOV and velocity;
Choose panoramas for the output using shortest path
in graph algorithm;
Construct the panoramas; F
Stabilize and crop;

panoramas. Perspective images can be aligned and warped using simple 2D transformations. An example of a cropped panoramic image after removal of lens distortion is given in Figure 9. We use the method of [34] to remove lens distortion. Usually, frames are cropped after the lens distortion removal to a rectangle containing only valid pixels. However, in the case of panoramas, the cropping may be done after stitching the frames. This results in even larger field of view.

We list the steps to generate Panoramic Hyperlapse in Algorithm 1.

6 PANORAMIC HYPERLAPSE OF MULTIPLE VIDEOS

Panoramic Hyperlapse can be extended naturally to multiple input videos. The first step in the process of creating Panoramic Hyperlapse from multiple videos is finding corresponding frames across videos, followed by panorama creation.

6.1 Correspondence Across Videos

As the first stage in multi-video hyperlapse, for every frame in each video we try to find corresponding frames in all other videos. When a group of people are walking together, matching frames can be defined as those frames captured at the same time. But in general such temporal alignment is rare, and instead corresponding frames can be defined as frames captured from the same location, or frames viewing the same region.

For our experiments, we defined as matching frames those frames having the largest region of overlap, measured by the number of matching feature points between the frames. We use coarse-to-fine method, i.e. given a frame in one video we first find an approximate matching frame in the second video, then narrowing the gap and finding an exact match. Some frames in one video may not have corresponding frame in the second video, since we required a minimal number of corresponding feature points for correspondence. In current experiments we required at least 10 corresponding points.



Fig. 10. Creating a multi-video Panoramic Hyperlapse. The first three rows indicate three input videos with frames labeled V_{ij} . Each frame P_i in the output panoramic video is constructed by mosaicing one or more of the input frames, which can originate from any input video.



Fig. 11. A multi-video output frame. All rectangles with white borders are frames from the same video, while the left part is taken from another. Notice the enlarged field of view resulting from using frames from multiple videos.

We also maintain temporal consistency in the matching process. For example, assuming x' and y' are the corresponding frame numbers in the second video for frame numbers x and y in the first video. If x > y, then we also require that x' > y'. Temporal consistency may reduce the number of corresponding frames.

6.2 Creation of Multi-Video Panorama

Once the corresponding frames have been identified, we initiate the process of selecting central frames. This process is done independently for each video as described in Sec. 5.

Following the selection of central frames the panoramas are constructed. In this step frames from all input videos are used. Consider the scenario when we have n input videos and we are creating a panorama corresponding to a temporal window ω in one of the videos. Originally, all frames of that video in the temporal window ω participated in that panorama. In the multi video case each participating frame brings together with it to the panorama also all frames corresponding to it in other videos. In our example having n videos, up to $(n \cdot |\omega|)$ frames may participate in each mosaic.

The process of panorama creation is repeated for all temporal windows in all input videos. Fig. 10 outlines the relation between the Panoramic Hyperlapse and the input videos.

6.3 Multi-Video Hyperlapse

After creating panoramas in each video, we perform a sampling process similar to the one described in Sec. 5.2. The

Algorithm 2: Multi video Panoramic Hyperlapse

5 71 1
Data: Multiple videos
Result: Panoramic Hyperlapse
Preprocess: temporally align videos (if necessary);
calculate homographies between matching frames in
different videos;
for each video do
Find central frames and calculate cost similar to
the single video case;
Calculate cross-video cost ;
Choose panoramas for the output using shortest path
in graph algorithm;
for each panorama with center c do
for every frame f from c's video participating in the
panorama do
warp f towards c ;
for frames f' aligned with f in other videos do
warp f' towards c using chained
homography f' - f - c ;
\Box = Construct the paperameter
Stabilize and crop;

difference being that the candidate panoramas for sampling come from all the input videos. The graph creation process is the same with the nodes now corresponding to panoramas in all the videos. For the edge weights, apart from the costs as mentioned in the last section, we insert an additional term called *cross-video* penalty. Cross-video terms add a switching penalty, if in the output video there is a transition from panorama with central frame from one video to a panorama with central frame that comes from some other video.

The shortest path algorithm then runs on the graph created this way and chooses the panoramic frames from all input videos. We show a sample frame from one of the output videos generated by our method in Fig. 11. Algorithm 2 gives the pseudo code for our algorithm.

7 EXPERIMENTS

In this section we give implementation details and show the results for EgoSampling as well as Panoramic Hyperlapse. We have used publicly available sequences [12], [35], [36], [37] as well as our own videos for the demonstration. The details of the sequences are given in Table 1. We used a modified (faster) implementation of [4] for the LK [38] optical flow estimation. We use the code and calibration details given by [8] to correct for lens distortion in their sequences. Feature point extraction and fundamental matrix recovery is performed using VisualSFM [39], with GPU support. The rest of the implementation (FOE estimation, energy terms and shortest path etc.) is in Matlab. All the experiments have been conducted on a standard desktop PC.

7.1 EgoSampling

We show results for EgoSampling on 8 publicly available sequences. For the 4 sequences for which we have camera calibration information, we estimated the motion direction based on epipolar geometry. We used the FOE estimation Sequences used for the fast forward algorithm evaluation. All sequences were shot in 30fps, except 'Running' which is 24fps and 'Walking11' which is 15fps.

Name	Src	Resolution	Num Frames
Walking1	[12]	1280x960	17249
Walking2	[40]	1920×1080	2610
Walking3	[40]	1920×1080	4292
Walking4	[40]	1920×1080	4205
Walking5	[37]	1280x720	1000
Walking6	[37]	1280×720	1000
Walking7	-	1280×960	1500
Walking8	_	1920×1080	1500
Walking9	[40]	1920×1080	2000
Walking11	[37]	1280x720	6900
Walking12	[4]	1920×1080	8001
Driving	[36]	1280x720	10200
Bike1	[12]	1280×960	10786
Bike2	[12]	1280×960	7049
Bike3	[12]	1280×960	23700
Running	[35]	1280x720	12900

method as a fallback when we could not recover the fundamental matrix. For this set of experiments we fix the following weights: $\alpha = 1000$, $\beta = 200$ and $\gamma = 3$. We further penalize the use of estimated FOE instead of the epipole with a constant factor c = 4. In case camera calibration is not available, we used the FOE estimation method only and changed $\alpha = 3$ and $\beta = 10$. For all the experiments, we fixed $\tau = 100$ (maximum allowed skip). We set the source and sink skip to $D_{start} = D_{end} = 120$ to allow more flexibility. We set the desired speed up factor to $10 \times$ by setting K_{flow} to be 10 times the average optical flow magnitude of the sequence. We show representative frames from the output for one such experiment in Fig.5. Output videos from other experiments are given at the project's website: http://www.vision.huji.ac.il/egosampling/.

7.1.1 Running times

The advantage of EgoSampling is in its simplicity, robustness and efficiency. This makes it practical for long unstructured egocentric videos. We present the coarse running time for the major steps in our algorithm below. The time is estimated on a standard Desktop PC, based on the implementation details given above. Sparse optical flow estimation (as in [4]) takes 150 milliseconds per frame. Estimating F-Mat (including feature detection and matching) between frame I_t and I_{t+k} where $k \in [1, 100]$ takes 450 milliseconds per input frame I_t . Calculating second-order costs takes 125 milliseconds per frame. This amounts to total of 725 milliseconds of processing per input frame. Solving for the shortest path, which is done once per sequence, takes up to 30 seconds for the longest sequence in our dataset ($\approx 24K$ frames). In all, running time is more than two orders of magnitude faster than [8].

7.1.2 User Study

We compare the results of EgoSampling, first and second order smoothness formulations, with naïve fast forward with $10 \times$ speedup, implemented by sampling the input

TABLE 2

Fast forward results with desired speedup of factor 10 using second-order smoothness. We evaluate the improvement as degree of epipole smoothness in the output video (column 5). Please refer to the text for details on how we quantify smoothness. The proposed method gives huge improvement over naïve fast forward in all but one test sequence ('Driving'), see Fig. 12 for details. Note that one of the weaknesses of the proposed method is lack of direct control over speedup factor. Though the desired speedup factor is 10, the actual frame skip (column 4) differs a lot from target due to conflicting constraint posed by stabilization.

Name	Input Frames	Output Frames	Median Skip	Improvement over Naïve $10 \times$
Walking1	17249	931	17	283%
Walking11	6900	284	13	88%
Walking12	8001	956	4	56%
Driving	10200	188	48	-7%
Bike1	10786	378	13	235%
Bike2	7049	343	14	126%
Bike3	23700	1255	12	66%
Running	12900	1251	8	200%

video uniformly. For EgoSampling the speed is not directly controlled but is targeted for $10 \times$ speedup by setting K_{flow} to be 10 times the average optical flow magnitude of the sequence.

We conducted a user study to compare our results with the baseline methods. We sampled short clips (5-10 seconds each) from the output of the three methods at hand. We made sure the clips start and end at the same geographic location. We showed each of the 35 subjects several pairs of clips, before stabilization, chosen at random. We asked the subjects to state which of the clips is better in terms of stability and continuity. The majority (75%) of the subjects preferred the output of EgoSampling with first-order shakiness term over the naïve baseline. On top of that, 68% preferred the output of EgoSampling using second-order shakiness term over the output using first-order shakiness term.

To evaluate the effect of video stabilization on the EgoSampling output, we tested three commercial video stabilization tools: (i) Adobe Warp Stabilizer (ii) Deshaker ² (iii) Youtube's Video stabilizer. We have found that Youtube's stabilizer gives the best results on challenging fast forward videos ³. We stabilized the output clips using Youtube's stabilizer and asked our 35 subjects to repeat process described above. Again, the subjects favored the output of EgoSampling.

7.1.3 Quantitative Evaluation

We quantify the performance of EgoSampling using the following measures. We measure the deviation of the output from the desired speedup. We found that measuring the speedup by taking the ratio between the number of input and output frames is misleading, because one of the features of EgoSampling is to take large skips when the magnitude



Fig. 12. A failure case for the proposed method. Two sample frames from the sequence. Note that the frame to frame optical flow computed for this sequence is misleading - most of the field of view is either far away (infinity) or inside the car. In both cases, its near zero. However, since the driver shakes his head every few seconds, the average optical flow magnitude is relatively high. The velocity term causes us to skip many frames until the desired K_{flow} is met, causing large frame skips in the output video. Restricting the maximum frame skip by setting τ to a small value leads to arbitrary frames being chosen looking sideways, causing shake in the output video.

of the optical flow is rather low. We therefore measure the effective speedup as the median frame skip.

Additional measure is the reduction in epipole jitter between consecutive output frames (or FOE if F-Matrix cannot be estimated). We differentiate the locations of the epipole (temporally). The mean magnitude of the derivative gives us the amount of jitter between consecutive frames in the output. We measure the jitter for our method as well for naive $10 \times$ uniform sampling and calculate the percentage improvement in jitter over competition.

Table 2 shows the quantitative results for frame skip and epipole smoothness. There is a huge improvement in jitter by our algorithm. We note that the standard method to quantify video stabilization algorithms is to measure crop and distortion ratios. However since we jointly model fast forward and stabilization such measures are not applicable. The other method could have been to post process the output video with a standard video stabilization algorithm and measure these factors. Better measures might indicate better input to stabilization or better output from preceding sampling. However, most stabilization algorithms rely on trajectories and fail on resampled video with large view difference. The only successful algorithm was Youtube's stabilizer but it did not give us these measures.

7.1.4 Limitations

One notable difference between EgoSampling and traditional fast forward methods is that the number of output frames is not fixed. To adjust the effective speedup, the user can tune the velocity term by setting different values to K_{flow} . It should be noted, however, that not all speedup factors are possible without compromising the stability of the output. For example, consider a camera that toggles between looking straight and looking to the left every 10 frames. Clearly, any speedup factor that is not a multiple of 10 will introduce shake to the output. The algorithm chooses an optimal speedup factor which balances between the desired speedup and what can be achieved in practice on the specific input. Sequence 'Driving' (Figure 12) presents an interesting failure case.

Another limitation of EgoSampling is to handle long periods in which the camera wearer is static, hence, the camera is not translating. In these cases, both the fundamental matrix and the FOE estimations can become unstable, leading to wrong cost assignments (low penalty instead of

²http://www.guthspot.se/video/deshaker.htm

³We attribute this to the fact that Youtube's stabilizer does not depend upon long feature trajectories, which are scarce in sub-sampled video as ours.

TABLE 3

One of the contributions of this paper is increased field of view (FOV) over existing sampling methods. To measure the improvement in FOV, we compare cropping of output frame by the proposed method for single input video. The percentages indicate the average area of the cropped image from the original input image, measured on 10 randomly sampled output frames from each sequence. The same frames were used to measure all five methods. The naive, EgoSampling(ES), and Panoramic Hyperlapse(PH) outputs were stabilized using YouTube stabilizer [16]. Real-time Hyperlapse [10] output was created using the desktop version of the Hyperlapse Pro. app. The output of Hyperlapse [8] is only available for their dataset. We observe improvements in all the examples except 'walking2', in which the camera is very steady.

Name	Exp. No.	Naive	[10]	[8]	ES	PH
Bike3	S1	45%	32%	65%	33%	99%
Walking1	S2	52%	68%	68%	40%	95%
Walking2	S3	67%	N/A	N/A	43%	66%
Walking3	S4	71%	N/A	N/A	54%	102%
Walking4	S5	68%	N/A	N/A	44%	109%
Running	S6	50%	75%	N/A	43%	101%

high) to graph edges. The appearance and velocity terms are more robust and help reduce the number of outlier (shaky) frames in the output.

7.2 Panoramic Hyperlapse

In this section we show experiments to evaluate Panoramic Hyperlapse for single as well as multiple input videos. To evaluate the multiple videos case (Section 6), we have used two types of video sets. The first type are videos sharing similar camera path on different times. We obtained the dataset of [40] suitable for this purpose. The second type are videos shot simultaneously by number of people wearing cameras and walking together. We scanned the dataset of [37] and found videos corresponding to a few minutes of a group walking together towards an amusement park. In addition, we choreographed two videos of this type by ourselves. We will release these videos upon paper acceptance. The videos were shot using a GoPro3+ camera. Table 1 gives the resolution, FPS, length and source of the videos used in our experiments.

7.3 Implementation Details

We have implemented Panoramic Hyperlapse in Matlab and run it on a single PC with no GPU support. For tracking we use Matlab's built in SURF feature points detector and tracker. We found the homography between frames using RANSAC. This is a time consuming step since it requires calculating transformations from every frame which is a candidate for a panorama center, to every other frame in the temporal window around it (typically $\omega = 50$). In addition, we find homographies to other frames that may serve as other panorama centers (before/after the current frame), in order to calculate the Shakiness cost of a transition between them. We avoid creating the actual panoramas after the sampling step to reduce runtime. However, we still have to calculate the panorama's FOV as it is part of our cost function. We resolved to created a mask of the panorama, which is faster than creating the panorama itself. The parameters of the cost function in Eq. (3) were set to

TABLE 4 Evaluation of the contribution of multiple videos to the FOV. The crop size was measured twice: once with the single video algorithm, with the video in the first column as input, and once with the multi video algorithm.

Name	Exp. No.	Ours Single	Number of Videos	Ours Multi
Walking2	M1	67%	4	140%
Walking5	M2	90%	2	98%
Walking7	M3	107%	2	118%

 $\alpha = 1 \cdot 10^7$, $\beta = 5 \cdot 10^6$, $\gamma = 1$ and $\lambda = 15$ for the crop window smoothness. Our *cross*-*video* term was multiplied by the constant 2. We used those parameters both for the single and multi video scenarios. The input and output videos are given at the project's website.

7.4 Runtime

The following runtimes were measured with the setup described in the previous section on a 640×480 resolution video, processing a single input video. Finding the central images and calculating the Shakiness cost takes 200ms per frame, each. Calculating the FOV term takes 100ms per frame on average. Finding the shortest path takes a few seconds for the entire sequence. Sampling and panorama creation takes 3 seconds per panorama, and the total time depends on the speed up from the original video i.e. the ratio between number of panoramas and length of the input. For a typical $\times 10$ speed this amounts to 300ms. The total runtime is 1.5-2 seconds per frame with an unoptimized Matlab implementation. In the multi-input video cases the runtime grows linearly with the number of input sequences.

7.5 Evaluation

The main contribution of Panoramic Hyperlapse to the hyperlapse community is the increased field of view (FOV) over existing methods. To evaluate it we measure the output resolution (i.e. the crop size) of the baseline hyperlapse methods on the same sequence. The crop is a side-effect of stabilization: without crop, stabilization introduces "empty" pixels to the field of view. The cropping ensures to limit the output frame to the intersection of several FOVs, which can be substantially smaller than the FOV of each frame depending on the shakiness of the video.

The crop size is not constant throughout the whole output video, hence it should be compared individually between output frames. Because of the frame sampling, an output frame with one method is not guaranteed to appear in the output of another method. Therefore, we randomly sampled frames for each sequence until we had 10 frames that appear in all output methods. For a panorama we considered its central frame. We note that the output of [8] is rendered from several input frames, and does not have any dominant frame. We therefore tried to pick frames corresponding to the same geographical location in the other sequences. Our results are summarized in Tables 3 and 4. It is clear that in terms of FOV we outperform most of the baseline methods on most of the sequences. The



Fig. 13. Two results comparing FOV of hyperlapse frames, corresponding to approximately same input frames. For best viewing zoom to 800%. <u>Columns:</u> (a) Original frame and output of EgoSampling. (b) Output of [8]. Cropping and rendering errors are clearly visible. (c) Output of [10] suffering from strong cropping. (d) Output of our method, having the largest FOV. <u>Top row:</u> Frames from sequence 'Bike1'. <u>Bottom row:</u> Frames from sequence 'Walking1'.



Fig. 14. Comparing field-of-view of panoramas generated from single (left) and multi (right) video Panoramic Hyperlapse. Multi video Panoramic Hyperlapse is able to successfully collate content from different videos for enhanced field of view.

contribution of multiple videos to the FOV is illustrated in Figure 14.

The naive fast forward, EgoSampling, and Panoramic Hyperlapse outputs were stabilized using YouTube stabilizer. Real-time Hyperlapse [10] output was created using the desktop version of the Hyperlapse Pro. app. The output of Hyperlapse [8] is only available for their dataset.

7.5.0.1 Failure case: On sequence Walking2 the naive results get the same crop size as our method (see Table 3). We attribute this to the exceptionally steady forward motion of the camera, almost as if it is not mounted on the photographer head while walking. Obviously, without the shake Panoramic Hyperlapse can not extend the field of view significantly.

7.6 Panoramic Hyperlapse from Multiple Videos

Fig. 14 shows a sample frame from the output generated by our algorithm using sequences 'Walking 7' and 'Walking 8'. Comparison with panoramic hyperlapse generated from single video clearly shows that our method is able to assemble content from frames from multiple videos for enhanced field of view. We quantify the improvement in FOV using the crop ratio of the output video on various publicly and self shot test sequences. Table 4 gives the detailed comparison. Multi Video Panoramic Hyperlapse can also be used to summarize contents from multiple videos. Fig. 15 shows an example panorama generated from sequences 'Walking 5' and 'Walking 6' from the dataset released by [37]. While a lady is visible in one video and a child in another, both persons appear in the output frame at the same time.

When using multiple videos, each panorama in the Panoramic Hyperlapse is generated from many frames, as much as 150 frames if we use three videos and a temporal window of 50 frames. With this wealth of frames, we can filter out some frames with undesired properties. For example, if privacy is a concern, we can remove from the panorama all frames having a recognizable face or a readable license plate.

8 CONCLUSION

We propose a novel frame sampling technique to produce stable fast forward egocentric videos. Instead of the demanding task of 3D reconstruction and rendering used by the best existing methods, we rely on simple computation of the epipole or the FOE. The proposed framework is very efficient, which makes it practical for long egocentric videos. Because of its reliance on simple optical flow, the method



Fig. 15. Multi video Panoramic Hyperlapse can be used to summarize content from multiple videos. Left and middle are two input spatially neighboring frames from different videos. Right is the output frame generated by Panoramic Hyperlapse. The blue lines indicate frames coming from the same video as the middle frame (Walking6), while the white lines indicate frames from the other video (Walking5). Notice that while a lady can be observed in one and a child in another, both are visible in the output frames. The stitching errors are due to misalignment of the frames. We did not have the camera information for these sequences and could not perform lens distortion correction

can potentially handle difficult egocentric videos, where methods requiring 3D reconstruction may not be reliable.

We also present Panoramic Hyperlapse, a method to create hyperlapse videos having a large field-of-view. While in EgoSampling we drop unselected (outlier) frames, in Panoramic Hyperlapse, we use them to increase the field of view in the output video. In addition, Panoramic Hyperlapse naturally supports the processing of multiple videos together, extending the output field of view even further, as well as allowing to consume multiple such videos in less time. The large number of frames used for each panorama also allows to remove undesired objects from the output.

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