# MoViMash: Online Mobile Video Mashup

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## ABSTRACT

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With the proliferation of mobile video cameras, it is becoming eas- ier for users to capture videos of live performances and socially share them with friends and public. As an attendee of such live performances typically has limited mobility, each video camera is able to capture only from a range of restricted viewing angles and distance, producing a rather monotonous video clip. At such per- formances, however, multiple video clips can be captured by differ- ent users, likely from different angles and distances. These videos can be combined to produce a more interesting and representative mashup of the live performances for broadcasting and sharing. The earlier works select video shots merely based on the quality of cur- rently available videos. In real video editing process, however, recent selection history plays an important role in choosing future shots. In this work, we present MoViMash, a framework for automatic online video mashup that makes smooth shot transitions to cover the performance from diverse perspectives. Shot transition and shot length distributions are learned from professionally edited videos. Further, we introduce view quality assessment in the framework to filter out shaky, occluded, and tilted videos. To the best of our knowledge, this is the first attempt to incorporate history based diversity measurement, state-based video editing rules, and view quality in automated video mashup generations. Experimental results have been provided to demonstrate the effectiveness of MoViMash framework.

**Categories and Subject Descriptors:** I.2.10 [Vision and Scene Understanding]: Video Analysis



**General Terms:** Algorithms, Design.

**Keywords:** Mobile Video, Virtual Director, Video Mashup.

## 1. INTRODUCTION

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Worldwide shipment of camera phones were estimated to reach 1.14 billion in the year 2011 alone [1]. Furthermore, a survey of over 2,500 respondents by Photobucket reveals that 45spondents use mobile devices to shoot video at least once weekly during the summer of 2011, validating the significant increase in the amount of mobile video uploaded to PhotobucketâĂŹs video sharing website (14ÃŮ in Summer 2011 compared to December 2010) [2].

Proliferation of such mobile devices with video capture capability has enabled users to capture video of their life events such as concerts, parades, outdoor performances, etc, and socially share them with friends and public as it happens. Videos recorded by a single user at such events are shot from a limited range of angles and distances from the performance stage, as an attendee typically has limited mobility (e.g., constraint by seating arrangement). The recorded video can be monotonous and uninteresting. Further more, videos recorded are typically short (in the order of minutes or tens of minutes), due to tired arms or power constraint of mobile devices. There are, however, likely to have more than one users recording the same performance from different angles at the same time, especially at a well-attended performance.

These recorded and shared video clips of the same performance can be cut and joined together to produce a new mashup video, similar to how a TV director of a live TV show would switch between different cameras to produce the show. Generation of a video mashup can be cast as a video selection problem: given a set of video clips capturing the same performance event, automatically select one of the video clips at any one time instance to be included in the output mashup video.

In this paper, we introduce MoViMash, our approach to solve the above video selection problem. MoViMash aims to produce mashup video from a set of mobile devices that is interesting and pleasing to watch, and uses a combinations of content-analysis, state-based transitions, history-based diversity, and learning from human editors to achieve this goal. We now provide an overview of how MoViMash works in the usual setting of live performances, shown in Figure 1. There is generally a staging area and an audience area where the audiences either sit or stand to watch the performance, and record the performance with a mobile device. This setting poses a few challenges to video mashup.

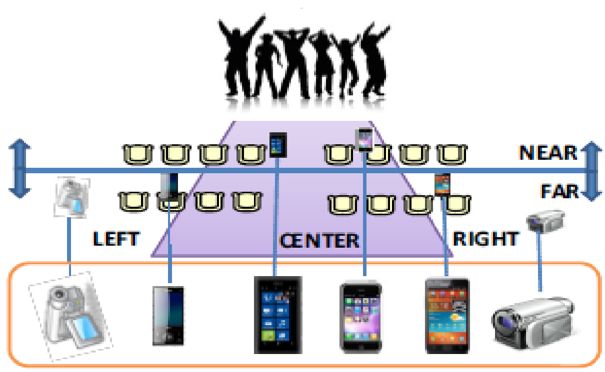


**Figure 1: A general performance scenario**

Since the videos are recorded with a hand-held mobile device, from the audience area, and likely by non-professional, there is no guarantee on the view quality. The videos can be shaky or tilted. Furthermore, it is common to include the back of the head of other audiences in the view. As other audiences move, the view can be temporarily occluded. When MoViMash needs to decide which video to select, it first filters out the videos with bad views currently from further consideration for selection. To achieve this, MoVi-Mash analyzes the video to determine the current shakiness, the tilt angle, and the level of occlusion in the video. Note that shakiness and tilt angle can be obtained from easily sensory data of mobile device when available.
The shooting angle of the remaining videos are then classified as either center, left, and right; and distance from the stage as near and far as shown in Figure 1. This classification is done every time we perform video selection because mobile users may change their position over time. MoViMash now decides which shooting angle and distance should be used; and for how long the selected class should persist. To this end, MoViMash tries to imitate a professional video editor, by using a finite state machine, whose transition probabilities are learned from analyzing professionally edited videos of the same type of event. The rationale behind the inclusion of learning is that, we have observed that there are no generic editing rules that can be precisely defined to work with all types of events. The video editors make fine decisions such as shot lengths and transitions based on their experience which is hard to enumerate.
The videos from the selected class are further ranked based on the video quality and diversity values to make the final selection. To consider video quality, MoViMash favors video with low blurriness, low blockiness (good compression), good contrast, and good illumination in each video. To consider diversity, MoViMash stores a history of recent video selections and favors videos with dissimilar views with recent selections.
We have developed MoViMashâĂŹs algorithm such that it is online and only depends on history information. As such, even though it is not our main goal in this paper, MoViMash can be applied to mashup of live video feeds from mobile devices.
We now briefly compare MoViMash to existing work to highlight the contribution of this paper. There has been few works on video selection in a lecture broadcast and video streaming [21] [6] and video conferencing [3]. In these works the camera is mainly selected based on speaker detection. Live performances are not speaker centric. In fact, the speech signals are generally noise from the crowd. In one recent work, Shrestha et al. [15] propose a method to create a video mashup from a given set of concert recordings. In that work, the authors select the shots based on mainly video quality, mostly ignoring view quality. Also, the diversity is only calculated based on the comparison of the last image of the current shot and first image of the next shot. It does not consider the history of video selection and the time for which a particular camera is selected. Further, video editing rules, which are subtle in the case of live performances, are not considered.
**Contributions.** We now summarize our contributions in this paper as follows:

- We propose a state-based approach for shot selection that incorporates the selection history in the decision process. Earlier methods select shots based on only currently available.
- We include view quality in the framework to filter out the bad views that are occluded, tilted, or shaky. Earlier methods only considered video quality.
- We build a comprehensive model to calculate diversity that considers both previously selected videos and shot lengths.
- We propose a learning-based approach where the shot transition probabilities and shot lengths are learned from professionally edited videos.

**Organization.** The rest of the paper is organized as follows. We provide a review of earlier work in Section 2. In Section 3 we describe proposed mashup framework. We evaluate our system in Section 4. The conclusions are provided in Section 5.

## 2. PREVIOUS WORK

There has been only few works on online camera selection. In most of these works, videos are mainly selected to show the speak- ers. In the work by Machnicki and Rowe [9], an online lecture webcast system is presented in which the cameras that are focusing on speaker and the presentation (the screen) are selected iteratively until anybody from audience asks question. When audience ask question, the camera that is focusing the person asking question is selected. The automatic selection of cameras in a lecture webcast is extended by Zhang et al. [21] to include audio based localization and

**Table 1: A Comparison of Previous Work**

| Work | Online | Diversity | Learning | Video Quality | View Quality | Scenario |
|---|---|---|---|---|---|---|
| Machnicki et al.[9] | Yes | No | No | No | No | Lecture webcast |
| Machnicki et al.[9] | Yes | No | No | No | No | Lecture webcast |
| Machnicki et al.[9] | Yes | No | No | No | No | Lecture webcast |
| Machnicki et al.[9] | Yes | No | No | No | No | Lecture webcast |
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| Machnicki et al.[9] | Yes | No | No | No | No | Lecture webcast |
| Machnicki et al.[9] | Yes | No | No | No | No | Lecture webcast |

speaker tracking. Similar approach is taken by Cutler et al. [6] in a meeting scenario where camera that shows the current speaker is selected. Ranjan et al. [12] use face tracking and audio analy- sis to show the close-up of the person talking. Since performers play more important role than speakers in live concerts, a speaker based selection is not appropriate. Further, the faces are generally far from the camera which cannot be detected. Therefore, face detection is not a reliable basis to select videos.

Al-Hames et al. [3] extends the camera selection work to include the motion features. We do not use motion features in our framework because both performers and audience generate continuous motion. Also, the movement of the mobile camera can inject erroneous motion in the video, which is aesthetically appealing. Yu et al. [20] propose to customize the camera selection and shot lengths based on user preferences. At every lecture webcast receiving site, the user can give score to the videos and specify rules for shot lengths. While such an interactive selection of cameras is useful for educational scenarios, people may find it annoying and stressful for performances, particularly when the number of videos is large.

A camera selection method for sports video broadcast is proposed by Wang et al. [16]. The authors assume one main camera and other sub cameras. The empirical main camera duration is found to be from 4 to 24 seconds, and sub camera duration is found to be 1.5 to 8 seconds. They select a sub camera based on the clarity of the view, determined using motion features. In our work, along with shakiness of the videos, we also calculate view quality in terms of occlusion and rotation; and video quality in terms of contrast, blur, illumination, and blockiness. We also include explicit measurement of diversity in the framework. Engstrom et al. [8] discuss automatic camera selection for broadcast in a sports event capture scenario. The work mainly promotes collaborative video production, i.e., video recorded by production team as well as the consumers.

In other media production applications, the shots are selected to convey the story to the audience. For instance, de Lima et al. [7] propose a method to automatically select shots from multiple cameras for storytelling, according to the rules provided by the director. These methods are not useful for us as live performances generally do not have any story.

Recently, there has been works on creating video mashups from given set of videos. In one of the most recent works [15], Shrestha et al. select the cameras based on video quality. Although the authors refer to term âĂŸdiversityâĂŹ in the paper, it is merely a comparison of current frame and the next frame of the corresponding camera. The authors completely ignore the selection history and the time for which each view is selected. The authors also ignore editing rules corresponding to different views, which we incorporate through learning based classification and selection. Furthermore, unlike the method proposed in this paper, the authors rely on the future video for current shot selection. While this approach is fine for combining stored videos, it is not suitable for live applications such as broadcasting and live sharing.

We have provided a comparison of the related work in Table 1. The works have been compared with respect to the following aspects: (1) can the method be applied online (a method that uses future information cannot be applied online)? (2) is selection history based diversity considered? (3) is learning incorporated? (4) is video quality (clarity, contrast etc.) considered? (5) is view quality (view occlusion, tilted view etc.) considered? and (6) what is the underlying application scenario? It can be easily seen that the proposed method is the first attempt to consider history based diversity through learning for online video selection for live performances.

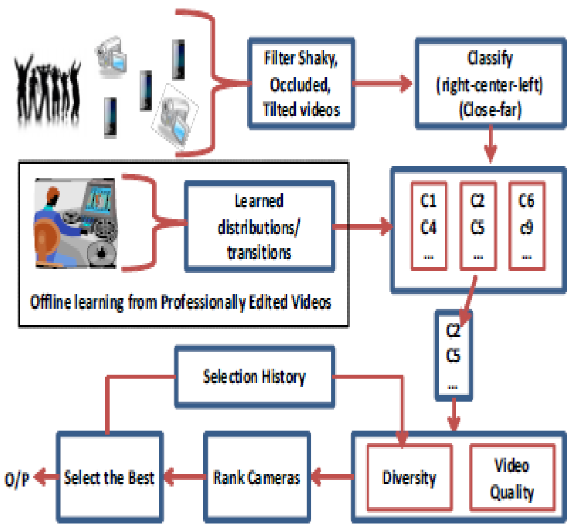


**Figure 2: The virtual director framework**

# 3. MOVIMASH FRAMEWORK

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In this section, we first enumerate the design principles that we have followed in the development of MoViMash and then describe the framework. After an overview of MoViMash, we focus on in- dividual components.

## 3.1 Design Principles

The end goal of the MoViMash is to produce a mashup that users like. To achieve this goal, we have followed a set of design principles as follows:

- **Video Quality:** In our discussion, video quality includes sharpness, contrast, illumination, and blockiness (due to video compression). A good image quality gives pleasing experience to the viewers [10]. Therefore, in our framework we give priority to good quality videos
- **View Quality:** A video that is captured by a tilted camera (rotated around horizontal axis) may have very good video quality, yet, users generally do not like tilted views. Similarly, a view in which a person or object is occluding stage area (blocking performance view) may be annoying to the user. Therefore view quality is also important. We measure view quality in terms of occlusion, tilt, and shakiness.
- **Diversity:** While static cameras always record videos from same perspective, mobile users generally shoot videos from a number of views and diverse perspectives. We take this opportunity to include more diversified views in the mashup. Both temporal and spatial aspects of diversity are considered in the proposed framework.
- **Learning:** When professionals edit the videos, they make many decisions based on their experience. Such decisions include shooting angle, distance from the stage, and shot length. It is, however, difficult to precisely state this experience in terms of hard-coded rules. Therefore, in this work, we learn the shot transitions and lengths from professionally edited videos.

The above mentioned design principles are met in our framework through various quality metrics and video selection/filtering phases, as described in the following section.

## 3.2 Framework

At every time instant, we have a number of videos to choose from. Once we have chosen the video, we also need to decide when to switch to another video. Hence, there are two main questions involved here that need to be answered for combining videos: (1) which video to select? (2) when to switch to another video? We use a three-phase method to select the video while the length is determined based on learned editing rules and overall quality score of the selected video.

Figure 2 shows the block diagram of overall framework. The proposed framework consists of one offline learning phase and three online selection phases namely filtering, classification, and selection. At any given time, the following steps are taken to select the most suitable video at current instant:

1. **Filtering:** In the filtering step, we determine videos that are unusable by comparing occlusion, shakiness, and tilt scores against empirically determined thresholds. The remaining videos are passed to the classification stage.
2. **Classification:** The selected cameras are classified as one of right, center, and left according to the capturing angle. Further, according to the viewing distance from the stage, they are classified as near or far.
3. **Class Prediction:** According to the class of currently selected video, and class transition probabilities learned from professionally edited videos, a most suitable class is predicted and videos from that class are selected for further con- sideration.
4. Video Selection: The classified cameras are further ranked with respect to a combined score of video quality, diversity, and shakiness. The video with highest score is selected.
5. **Shot Length:** The length of the video is selected based on learned distributions and video quality. A higher quality video is generally selected for longer time.

While filtering and selection phase ensure view and video quality, the classification and diversity ensure that we select videos recorded with different angles and viewing distances to provide a complete and interesting coverage of the performance. We now describe each component of the framework in detail.

## 3.3 View Quality

The view quality is measured in terms of three characteristics: occlusion, shakiness, and camera tilt. The details of measurement of each of these quantities is given below.

### *3.3.1 Occlusion*

For both a stand mounted camera and a mobile camera, there is always a chance of view occlusion. At crowded places, people sometime do not notice the cameras recording the video and occlude the performance view. Even if people notice the cameras, they stand in front of or walk across the cameras, because the main purpose of the performances is to entertain the audience who are present at the venue rather than video recording. Therefore, we detect the videos which are recorded by occluded cameras and filter them out.

Occlusion detection methods are popular in the field of object tracking [13, 19]. There methods employ various appearance models to seamlessly track multiple objects. In this case, the occlusion occurs when an object is hidden behind another. In live performances, this could be intentionally done by the performers, i.e., one performer coming in front of other. We are more interested in detecting the audience blocking the view. Therefore, those works are not applicable here.

We have developed an edge density based method to detect videos with occluded views. The method is based on the assumption that the objects that occlude the performance area will result in lower edge density than the performance area. Therefore, the non-occluded area of the image, which is far from the camera, will result in more dense edge points than the occluded area. To differentiate between homogeneous regions of the stage area, which could also have less edge density, and occluded area; we perform connected components on the edge image. Following are the steps of the occlusion detection in a given image I:

- Edge Detection: In the first step, we calculate the presence of an edge at each pixel location. Let $I^e$ be the resulting binary edge image

$$I^c(x,y) = \begin{cases} 1 & \text{if edge is detected at pixel } I(x,y) \\ 0 & \text{otherwise} \end{cases}$$

- Edge Density: We convolve the edge image with a square matrix W with all of its elements unity:

$$I^d = I^c \odot W$$

The output of the operation gives the density of edges around each pixel.

- Labeling the Patches: The image is now divided into patches of block size b × b. Each patch is labeled as 1 if the sum of edge densities is less that a threshold, else it is labeled as 0.

$$I^p(x^{'},y^{'}) = \begin{cases} 1 & \text{if the sum of edge densities in the patc} \\ 0 & \text{otherwise} \end{cases}$$

The 1's in the patch image shows potentially occluded regions.

- Connected Components: There can be homogeneous regions in the non-occluded area as well. These regions, however, are generally small. Therefore, connected components operation is performed to find the size of largest group of connected patches with label 1, which corresponds to occluded region.

- Occlusion Score: To calculate the final occlusion score S o , we first calculate the fractional occluded region f in the con- nected components output image, i.e.,

$$f = \frac{Noof1patches}{Totalnumberofpatches}$$

We also observed that generally the dynamic range of $f$ is very small. Therefore, we expand its range with an exponential function to calculate the final score $S^o$ :

$$S^o = 1 - e^- f$$

The resulting occlusion scores for an example video sequence are shown in the Figure 3. The sequence shows a person walking across a camera, which is recording an outdoor performance. We can see that as the person enters the camera view, the occlusion score starts increasing. We obtained similar results for night videos also, which are not shown due to space limitation. We found that for a patch size of 20*15 pixels, videos with occlusion score more than 0.2 are very bad, so these are filtered in the framework.

### 3.3.2 *Tilt*

In this work, we define tilt as the rotation of the camera around horizontal axis. User's generally do not like the videos recorded by tilted cameras. Therefore, we detect the tilted camera views and filter them. Here we use the heuristic that for a horizontally placed camera, most of the lines in the view are horizontal, while an inclined view generally has non-horizontal lines. The following steps are taken to calculation tilt:

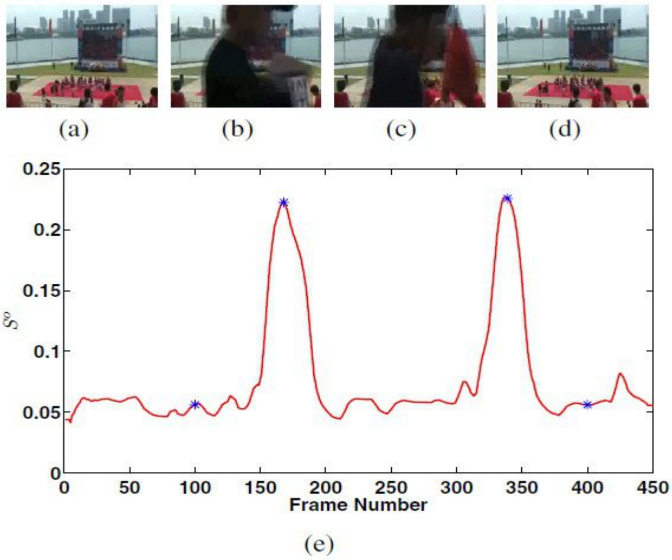



**Figure 3: Tilt results. Figures (a)-(d) show the frames 100, 186, 200, and 286 of the test video respectively. Figure (e) shows the corresponding tilt score**

- Line Detection: We use Hough transform to detect the straight line in the image. Let $l^{'}_i$ be the length of the $i^{th}$ line and $o^{'}_i$ the angle with respect to the horizontal line.

- Angle Restriction: We assume that the maximum tilt a camera can have is less than $\pi$ /4 and any line with the inclination above this angle is noise and not considered in calculation. Let the resulting orientation of $l^{'}_i$ line be $o_i$ .

- The final tilt score $S^t$ is calculated as absolute of the mean weighted orientation and normalized by $\pi/4$:

$$S^t = \frac{abs(\frac{1}{N^l})\sum_{i=1}^{N^l} o_i * l_i}{\pi/4}$$

where $N^l$ is the total number of lines in the image.

An example of tilt calculation is shown in Figure 4; the upper row shows frames from the video and the figure in lower row shows occlusion scores. The video clip is recorded by a mobile phone camera. In between, the mobile user gets engaged in some other activity, and the mobile phone gets tilted. We can observe in the frames itself the straight lines getting tilted. It gets reflected in the tilt score as shown in Figure 4 for frames 200 and 216. The videos with a tilt score of 0.4 are found unusable and they are filtered.

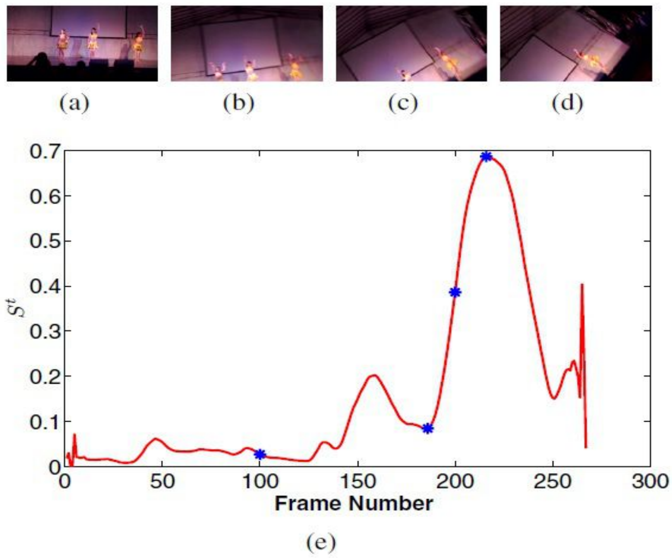



**Figure 4: Occlusion detection. Figures (a)-(d) show the frames 100, 168, 339, and 400 of the test video respectively. Figure (e) shows the corresponding occlusion score**

### *3.3.3 Shakiness*

Shakiness is calculated based on the method described in [4]. In this method, the pixel values are projected on horizontal and vertical axes. The horizontal and vertical projections are matched across the frames for calculating camera motion. A median filtered is finally applied on the motion vectors to differentiate the shaki- ness from the smooth camera motion. The final value of shakiness score, $S^s$ , is calculated by summing the absolute difference of orig- inal motion vector and median filtered motion vector. The score is normalized by calculating maximum difference empirically. For a shakiness window of 100 frames, the normalization value is 300; for any value above 300, S s is saturated to 1.

## 3.4 Learning

As mentioned earlier in Section 1, it is difficult to precisely enumerate all the rules which professional editors follow in selecting a video and its corresponding shot length. In MoViMash, we propose to learn the behavior of professional editor statistically for use in creating mashup. We use professionally edited videos for this purpose. The rules are learned in terms of shooting angle, shooting distance, and shot length. Following are the steps taken in the process of learning:

- At first, we divide the video into a sequence of shots and record shot length.
- Each shot is classified as right ($\mathcal{R}$), left ($\mathcal{L}$), or center (C) based on shooting angle (Figure 1).
- Depending on the distance of the recording device from the stage, the videos are further classified as near ($\mathcal{N}$) or far ($\mathcal{F}$) (Figure 1).
- Based on both classifications, we define six states (also re- ferred as classes in the paper) in which a video can be at any time instant, i.e., $\mathcal{CN}$ , $\mathcal{CF}$, $\mathcal{RN}$ , $\mathcal{RF}$, $\mathcal{LN}$ , and $\mathcal{LF}$ .
- From the sequence of the shots, we calculate the state transition probabilities for the above described six states.
- We now feed the transition probabilities (transition matrix) along with shot lengths (emission matrix) to an hidden Markov model (HMM). The HMM generates a sequence of shot states and their corresponding lengths.

$$
\begin{array}{c}
\\ \text{CN} \\ \text{CF} \\ \text{RN} \\ \text{RF} \\ \text{LN} \\ \text{LF}
\end{array}
\begin{array}{c}
\begin{array}{cccccc} \text{CN} & \text{CF} & \text{RN} & \text{RF} & \text{LN} & \text{LF} \end{array} \\
\begin{pmatrix}
0 & 0.4 & 0.2 & 0.1 & 0.2 & 0.1 \\
0.6 & 0 & 0.1 & 0.1 & 0.1 & 0.1 \\
0.5 & 0. & 0 & 0.1 & 0.2 & 0.1 \\
0.2 & 0.2 & 0.4 & 0 & 0.1 & 0.1 \\
0.4 & 0.2 & 0.2 & 0.1 & 0 & 0.1 \\
0.2 & 0.2 & 0.1 & 0.1 & 0.4 & 0
\end{pmatrix}
\end{array}
$$

$$
\begin{array}{c}
\\ \text{CN} \\ \text{CF} \\ \text{RN} \\ \text{RF} \\ \text{LN} \\ \text{LF}
\end{array}
\begin{array}{c}
\begin{array}{ccccccc} 1 & 2 & 3 & 4 & 5 & 6 & 7 \end{array} \\
\begin{pmatrix}
0 & 0.4 & 0.2 & 0.1 & 0.2 & 0.1 & 0.1 \\
0.6 & 0 & 0.1 & 0.1 & 0.1 & 0.1 & 0.1 \\
0.5 & 0. & 0 & 0.1 & 0.2 & 0.1 & 0.1 \\
0.2 & 0.2 & 0.4 & 0 & 0.1 & 0.1 & 0.1 \\
0.4 & 0.2 & 0.2 & 0.1 & 0 & 0.1 & 0.1 \\
0.2 & 0.2 & 0.1 & 0.1 & 0.4 & 0 & 0.1
\end{pmatrix}
\end{array}
$$

We use affine transformation to classify the video, giving an ac- curacy of ≡77% on our dataset. However, since learning is one time job, we performed manual classification of shots during the learning phase to get accurate statistics. Equation 7 shows the learned transition matrix while Equation 8 emission matrix. We have carefully selected five videos (live group dances with length of videos ranging from 210 to 300 seconds), which are profession- ally edited and aired on television. We downloaded these videos from YouTube. These videos include concerts by professional bands and performance at the Academy Awards ceremony. We observed that in dance videos, the shot lengths are relatively smaller ( average around 2.3 seconds) compared to solo singing videos ( average around 3.5 seconds). This finding implies that the learning dataset should comply with the type of performance for mashup. We also observed that the average shot lengths for all five dance videos ranged between 2.2 seconds to 2.4 seconds, showing little variations, which shows that a particular type of events have similar pattern of transitions and shot lengths which can be learned and applied to create online mashup.

## 3.5 Video Quality

We can have different quality videos because of the limitation of recording devices, varied camera positioning, lighting conditions, camera angle, and video recording skills of the person. To produce aesthetically beautiful video, it is important to consider the quality of the videos.We are considering the following aspects to obtain video quality score:

- **Blockiness** The blocking effect mainly comes due to poor quality of data compression. To measure blockiness, we take current image as sample and calculate its compression quality using the method described in [18]. The method generates a score that takes a value between 1 and 10 (10 represents the best quality, 1 the worst). We normalize the score between 0 and 1. Let $S^b$ be the blockiness score

- **Blur**: The video can be blurred due to many reasons such as out-of-focus recording, camera movement etc. We are calculating blur based on the method described in [5]. Let $S^{br}$ be the blur score which varies between 0 to 1 (0 represents blurred and 1 sharp).

- **Illumination**: There can be videos that are recorded in poor lighting conditions. The purpose of including this metric in quality measurement is to avoid selecting dark videos. The illumination score for the image $S^{im}$ (with width $N^w$ and height $N^h$ ) is calculated as average gray value, normalized by 255.

$$S^im = \frac{1}{255}\frac{1}{N^w * N^h}\sum_{x=0}^{N_w}\sum_{y=0}^{N_h}(I(x,y))$$

- **Contrast**: It has also been found in the literature that an image with good contrast is appreciated by the viewers [10]. Therefore, contrast is also chosen as one of the metrics. The contrast score S c is calculated as standard deviation of the pixel intensities.Contrast:

$$S^c = \frac{1}{255}\sqrt{\frac{1}{N^w * N^h}\sum_{x=0}^{N_w}\sum_{y=0}^{N_h}(I(x,y)-I)^2}$$

$\sum$

Its value varies from 0 to 1 where 1 is the desired value corresponding to high contrast.

- **Burned Pixels**: It has been identified that pixels that are close to 255 or 0 are generally not informative [15]. If N b is the number of such pixels, the quality score representing burnt pixels is calculated as follows:

$$S^{bp} = \begin{cases} 1 - \mathrm{N}^b/(0.25 - N^i) & \text{if } N^b/(0.25 * N^i) < 1 \\ 0 & \text{otherwise} \end{cases}$$

where $N^i$ is the total number of pixels in the image. In this case, a value of 1 represents best quality, i.e., no burnt pixels; while a value of 0 means at least 25

The individual quality scores are multiplied to calculate overall video quality score $S^q$ , i.e.,

$$S^q = S^b \times S^{br} \times S^{im} \times S^c \times S^{bp}$$

We have chosen to multiply the individual scores because we want to give priority to the videos that are good in all aspects.

## 3.6 Diversity

The aspect of diversity is included in the framework by calculatng the similarity of the views of the videos selected in the recent past. Let $\mathcal{H}$ be the history of the cameras that have been selected so far. The history is stored as set of chronologically order tuples, i.e.,

$$\mathcal{H} = \{(I_j^h, \triangle_j)|1 \leqslant j \leqslant N^v\}$$

where $N^v$ is the number videos selected in the recent past. Each tuple has the following two entries:

- $I^h$ - Snapshot from the selected cameras at the time of selection.

- $\triangle$ - The time for which the particular camera selected. It is normalized between 0 to 1 by dividing each video duration by the total time over which history is stored.

Let $VS$ be the view similarity matrix:

$$VS = \{v_{ij}|1 \leqslant i \leqslant n; 1 \leqslant j \leqslant N^v; \forall_i = j, v_{i,j} = 1\}$$

where n is number of cameras, and $v_{ij}$ is the view similarity measure between current frame from the $i^{th}$ video and $j^{th}$ frame of the history. The motivation of defining the view similarity $VS$ is to select video with different views. The overall steps of diversity calculation are as follows:

1. Determine the view similarity matrix V S by comparing cur- rent frame with the frames stored in the history, i.e.,

$$v_{ij} = D_iff(I_i^c, I_j^h)$$

   where $I_c^i$ is the current frame of $i^{th}$ camera, $I_h^j$ is the $j^{th}$ frame of the history, and $D_{if}f$ can be any function to calculate view similarity. We are using SSIM [17] for this purpose.

2. For the given content, the user interest decreases with time over which the user watches same or similar content. Hence, the diversity score of the $i^th$ video, i.e., $S^d$ is calculated for each of the current videos as follows

$$S^d = \sum_{j=1}^{N_v} v_{ij} * \triangle_j$$

3. Store the viewing time of the previous video and the current frame of the selected video in $\mathcal{H}$. If we choose a scheme where each camera is selected only for fixed amount of time, we may just store the current frame of the selected video.

The diversity scores for two candidate videos (Cam 1, Cam 2) and final mashup created using MoViMash for a performance (P3 in Table 2) are shown in the Figure 5. Although we are showing diversity for only two videos for clarity, there were five candidate videos in total. We can see that whenever a video gets selected, its diversity generally reduces, e.g., diversity of Cam 1 after Shot 8 and diversity of Cam 2

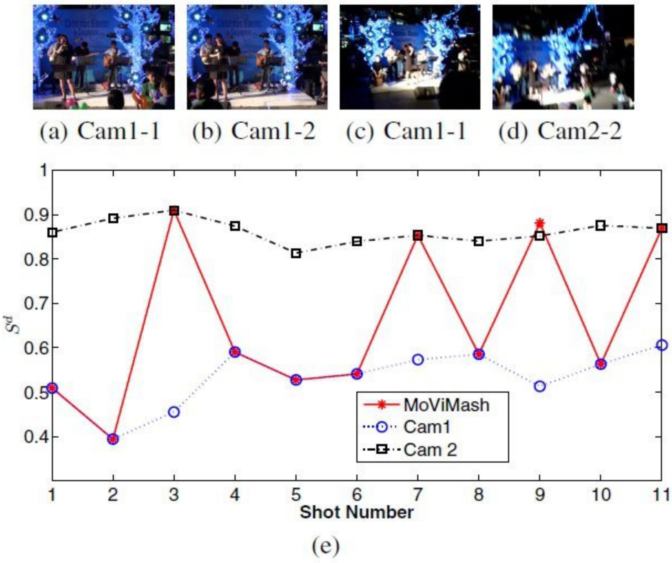



**Figure 5: Diversity value for two candidate videos and final mashup**

after Shot 3. At Shot 4, Cam 1 gets selected despite low diversity because its video quality is much better than others (Figure 5.a-b) with a stable view. Sometimes the diversity increases even when the video is currently selected (Shot 2, Cam 1) due to change in camera view, or when one of previous selections of the video moves out of history window. The diversity of Cam 2 decreases even though it is not selected. It is because during this time, its view is similar to Cam 1, resulting in large (near 1) value of v 12 (Equation 15). At Shot 9, a third (other than Cam 1 and Cam 2) video gets selected until Cam 1 diversity increases enough so that it gets selected again. In summary, the metric $S^d$ is able to capture and spatial and temporal diversity of videos.

### 3.7 Final Ranking

For all the videos of the selected class, we have three metrics: video quality score, diversity score, and shakiness score. We cal- culated weighted sum of these values to calculate final score $S^f$ :

$$S^f = \alpha_1 S^q + \alpha_2 S^d + \alpha_3 (1 - S^s)$$

where $\alpha_1$ , $\alpha_2$, and $\alpha_3$ are weighting coefficients and $\alpha_1 + \alpha_2 + \alpha_3 = 1$. In the experiments, we are using $\alpha_1 = \alpha_2 = \alpha_3$ ,which gives equal weightage to the quality, diversity, and stability of the videos. Nevertheless, these coefficients should be deter-mined based on the type of performance. For instance, in a hip-hop video mashup we can give less weightage to shakiness for better diversity and quality. A shaky video, however, can be annoying if the performance has smooth movements such as a tango performance. We therefore need to keep $\alpha_3$ higher in this case. Furthermore, if the videos are generally bad in the quality, we can give set high value for $\alpha_1$ . The shot from the video with the highest score is selected at the current time instant.

### 3.8 Length Selection

**Table 2: Details of data set**

| Performance | Type | Recordings | Duration (m) | Framerate |
|---|---|---|---|---|
| 11 | 21 | 31 | 41 | 15 |
| A1 | V2 | S3 | 4S | 5s |
| A1 | V2 | S3 | 4S | 5s |
| A1 | V2 | S3 | 4S | 5s |

To determine the switching instant, we are using a method which combines the learning based prediction to obey the editing rules and the superiority (in terms of overall quality) of the currently selected video. As discussed in the learning section (Section 3.4), every class of the videos follows a length distribution. For example the center videos are generally selected for longer duration while the left and right videos for relatively smaller duration.
Suppose the length predicted for the current class of the videos is $L^e$ . To accommodate the quality of the selected video in length calculation, we define bonus length $L^b$ . The purpose of the bonus length is to reward the high quality videos by extending their length. Suppose $S_1^f$ is the final combined score of the best camera and $S_2^f$ of the second best camera. Now the length for the currently selected video, $L^s$ , is determined as follows:

$$L^s = (1 - \varsigma)L^e + \varsigma L^b v$$

where is the difference of the scores, i.e., = $S_1^f - S_2^f$ and ς weighting coefficient. In our experiments, we found the empirical values of $L^b = 25$ and ςs well. A higher value of ςase impact of the bonus length $L^b$ on the selected shot length. In this way, ς stipulated to override the prediction made by learned statistics to select longer or shorter shots of given quality score $S^f$ .
In general cases, camera switching only takes place after the selected length of time. MoViMash, however, performs continuous check on occlusion and shakiness every second, and whenever the value goes above threshold (same as the one used in the filtering step), video selection is triggered. We added this optimization to take care of the situations where the view gets occluded after it is selection. While a lower video quality can still be acceptable, an occluded or shaky video annoys the viewers.

## 4. EVALUATION

its EVALUATION

The main goal of the experiments is to show that the proposed framework produces a mashup with better view quality and diver- sity than earlier works. In addition, we also compare our result with human-edited versions of mashups. The dataset consists of video recordings of four performances. For each performance, we cre- ate three mashups: (1) using proposed framework (MoViMash) (2) based on ranking average of shakiness, diversity, and video quality only (VQ-Only) (3) by human editor with editing experience (H- Edited). Users are asked to rate the quality of all three versions of mashup.

### 4.1 Dataset

The main application of the proposed framework is to

(a) P1-1 (b) P1-2 (c) P1-3 (d) P1-4

(e) P2-1 (f) P2-2 (g) P2-3 (h) P2-4

(i) P3-1 (j) P3-2 (k) P3-3 (l) P3-4

heightheight

**Figure 6: Selected frames from the recordings: (a-d) P1, (e-h) P2, (i-l) P3**

combine the videos recorded by mobile phone users. Therefore, we went to three public performances and handed over smart phones to the au- diences for recording. The audience were given a scenario where they were recording the video for sharing with their friends who were not present at the performance. All the performances hap- pened during the night time. The video clips are converted to a common resolution and synchronized before generating the mashups. In this work, we synchronized the videos manually as our main fo- cus is on video selection. The issue of automatic synchronization is being researched separately [14]. The details of the performances and video recordings are given in the Table 2. Figure 6 shows selected frames for each performance.

## 4.2 User Study

In the user study, we ask the users to watch the mashups created by the three methods and rate them accordingly. A total of seven- teen users participated in the study, with age range from 20 to 30. The users were mainly graduate students, males and females. The three methods used to create the mashups were not disclosed to the users. Further, the order of the videos produced by the different methods was randomized for different performances to reduce the bias the users may have due to particular presentation order.
The user study was conducted online with relevant instructions explained beforehand. It is told to the users that the "main purpose of this user study is to evaluate quality of video editing". Users were asked to rate three distinct performance (P1, P2 and P3). The three mashups (generated by MoViMash, VQ-Only and H-Edited) are juxtaposed on a website with questions below them. The users were allowed to replay the videos while answering the questions. The users rate the videos with a rating ranged between 1 to 5, where 1 represent worst and 5 being the best. The list of questions asked are given in Table 3.

**Table 3: User study questions**

| | |
|---|---|
| 11 | sdsadasdasdsad |
| A1 | sdsadasdasdsad |
| A1 | sdsadasdasdsad |
| A1 | sdsadasdasdsad |

## 4.3 Result Analysis

The average responses of the users, along with their standard deviations, are plotted in Figure 7 and Figure 8. We observed re- sponses of the users for Questions A,B,C,D to be similar and with slight variation for Question E.

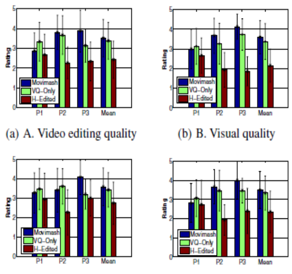
### 4.3.1 *Analysis of Questions A, B, C, and D*

We observed that majority of users responded homogeneously for all four of them. The responses indicated that the ratings were based on some distinct characteristics of the video. Based on addi- tional comments provided by the users, we infer that most of user ratings were based on the quality of the selected video and coverage of stage areas.
For P2 and P3, the users preferred the MoViMash created mashup. For both the performances, user's found the shot transitions to be smooth and pleasing. We relate this response of the user's to our class-based learning for predicting the shot transitions. The users also remarked that MoVi-

Mash produced videos had less occlusions in comparison with VQ-Only based mashup.
While users liked MoViMash created mashups of P2 and P3, they preferred VQ-Only mashup for P1. By analyzing the record- ings and user comments, we found that P1 differs from P2 and P3 in a common aspect. While P2 and P3 had a large number of similar quality videos to select from at each time instant, the videos record- ings of P1 were skewed with respect to quality. There were 2 to 3 videos which were stable and had very high video quality, whereas all other videos were relatively bad in quality. Since MoViMash attempts to maximize diversity along with video quality through class-based shot selection, sometimes poor quality videos are selected. On the other hand, P2 and P3 had many similar quality videos to choose from, which allowed MoViMash to select videos of dif- ferent classes with smooth transitions. Therefore, in the scenarios where the quality of videos is skewed with only few good quality videos, our MoViMash should be tuned to give more priority to the quality rather than smooth transitions. The further tuning can be done by selecting video from multiple future classes. However, with proliferation of mobile camera, we envision that in future the number of video recording will increase. An increased number of recordings will ensure that there are sufficient number of reason- ably good quality videos to ensure diversity of shots and smooth transitions. The human-edited version received lowest ratings for all three performances. After discussing with the human editor, we found that most of video editing techniques they learn assume availability of high quality videos. The video artifacts such as small camera shake, illumination variation etc. are generally negligible in these high quality videos. Therefore, they are generally not comfortable with the videos captured by mobile devices. Further, it would be very difficult for a human editor to evaluate and precisely compare quality of videos, particularly when the number of videos is large. The performance of video editors can get even worse when they have to make video selection in real-time. This finding makes a strong case for automated mashup creation for live applications of video sharing and broadcasting.

### 4.3.2 Overall Video Quality

User ratings for overall video quality are shown in the Figure 8. We can see that on average, MoViMash outperforms other meth- ods in overall video quality. Users generally liked the quality of videos created by MoViMash for all three performances. Further, the user ratings related to MoViMash had the least standard devi- ation among all three mashups. This result implies that the users had highly correlated opinion about the superiority of MoViMash. According to the comments users provided to justify their overall video quality ratings, they liked following things about MoViMash: complete coverage (from many angles), smooth shot transitions, less occlusion, and balanced camera selection. Yet, there might be instances where the semantics of the video govern the video selection, e.g., celebrity appearance, funny behavior by crowd, in- teresting gestures and expressions by audiences, etc. It is hard for the proposed automatic system to identify these instances; and a human can be introduced in the selection to improve the mashup quality in such scenarios.
It is important to note that although many users liked VQ-Only created videos more than MoViMash, they did not specify any con- crete aspect they liked about the video except selection of less shaky videos. Thus, for the given dataset, even though VQ-Only method is also able to produce videos with reasonable good quality, it will fail in many real scenarios as it does not have any provision for view quality and smooth shot transitions.



(a) A. Video editing quality (b) B. Visual quality

(c) C. Camera positioning (d) D. Interestingness

**Figure 7: User responses for questions A, B, C, and D**

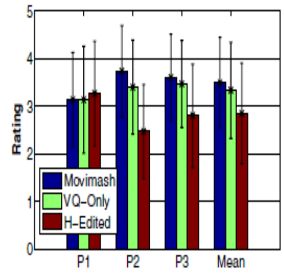



**Figure 8: User response on overall quality of video**

## 4.4 Discussion

The MoViMash framework takes automatic mashup creation meth- ods closer to the human editors. It, however, adds to the processing cost. The enhanced diversity model requires more memory for storing the history and more number of comparisons. Similarly, occlusion and tilt also require data processing that would have quadratic complexity in terms of the number of pixels in the image. Therefore, individual components of the framework could be enabled or disabled depending on the quality of the candidate videos. For ex- ample, if the videos are taken from the stand-mounted cameras, shakiness calculation can be omitted. Furthermore, to make the system scalable, we can process downscaled images as the video resolution is not critical for the current system components.

# 5. CONCLUSIONS FUTURE WORK

its CONCLUSIONS FUTURE WORK

In this paper, we have proposed and validated an online video mashup creation framework, MoViMash, for videos recorded by mobile devices. Based on the experiments and user study, we make following conclusions:

- MoViMash creates better quality mashups in comparison to human editor, and other methods that are mainly based on video quality.

- Proposed learning framework is able to imitate professional editorâĂŹs experience to have smooth shot transitions in the final mashup. The proposed framework is most effective when there are a number of similar visual quality videos to chose from.
- Human editors are not comfortable in editing videos that are recorded by mobile devices, particularly when there are large number of videos with varying quality.
- Proposed diversity model is able to incorporate both temporal and spatial aspects of the selection history.

In the future, we want to extensively evaluate individual com- ponents of the system with respect to end-to-end system delay and output mashup quality. As current mobiles are capable of record- ing full HD video, we want to insert artificial zoom and pan in the mashup using zoomable video techniques [11]. Further, a human director can only compare a limited number of videos at a time. A powerful computer, however, can process and compare a large number of videos simultaneously. Therefore, in the future we want to study the impact of the number of videos on the quality of the final mashup.

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## 6. REFERENCES

[1] http://www.bloomberg.com/news/2011-04-07/high-resolution-cameras-will-drive-mobile-phone-shipments-above-1-billion.html.

[2] Albert Einstein. *Zur Elektrodynamik bewegter Körper*. (German) [*On the electrodynamics of moving bodies*]. Annalen der Physik, 322(10):891âĂŞ921, 1905.

[3] http://www.businesswire.com/news/home /20110829005068/en/photobucket-survey-video-uploads-mobile-devices-rise

[4] M. Al-Hames, B. HÃűrnler, C. Scheuermann, and G. Rigoll. Using audio, visual, and lexical features in a multi-modal virtual meeting director. In Proc. of Machine Learning for Multimodal Interaction, pages 63âĂŞ74. Springer, Bethesda, MD, USA, May 2006.

[5] M. Campanella, H. Weda, and M. Barbieri. Edit while watching: home video editing made easy. In Proc. of SPIE 19th Ann. Symp. Electronic Imaging, Multimedia Content Access: Algorithms and Systems, volume 6506, page 21, San Jose, CA, USA, January 2007.

[6] F. Crete, T. Dolmiere, P. Ladret, and M. Nicolas. The blur effect: perception and estimation with a new no-reference perceptual blur metric. In Proc. of SPIE Human Vision and Electronic Imaging XII, volume 6492, San Jose, CA, USA, January 2007.