User-driven mobile robot storyboarding: Learning image interest and saliency from pairwise image comparisons

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Abstract—This paper describes a novel storyboarding scheme that uses a model trained on pairwise image comparisons to identify images likely to be of interest to a mobile robot user. Traditional storyboarding schemes typically attempt to summarise robot observations using predefined novelty or image quality objectives, but we propose a user training stage that allows the incorporation of user interest when storyboarding. Our approach dramatically reduces the number of image comparisons required to infer image interest by applying a Gaussian process smoothing algorithm on image features extracted using a pre-trained convolutional neural network. As a particularly valuable by-product, the proposed approach allows the generation of user-specific saliency or attention maps.

I. INTRODUCTION

Autonomous mobile robots can facilitate search and rescue operations and infrastructure inspection in potentially unsafe and dangerous areas. These robots often produce a large number of images of environments, providing useful ancillary information for human operators.

Unfortunately, the process of sifting through this large and rich amount of information is time consuming and laborious, requiring a great deal of care and concentration from the operators. As a result, a mechanism by which the information obtained is sorted and ranked according to usefulness or potential interest is highly desirable, since this would greatly alleviate the cognitive burden placed on operators. This paper introduces an interest detection algorithm suitable for automatic, user-driven video summarisation.

Our approach uses operator-intent-based pairwise image comparisons (see Figure 1) to estimate image interest by means of a standard probabilistic ranking scheme, TrueSkill™ [1]. We improve upon this scheme by incorporating a posterior Gaussian process (GP) regressor that estimates interest based on image similarities. These similarities are determined using image features extracted by a pre-trained convolutional neural network (CNN). Our approach is not only able to flag images of interest to a user, but also generates a saliency or attention map that incorporates user interest.

This paper is organised as follows. Section II discusses related work in novelty detection, storyboarding and saliency, while section III-A introduces probabilistic ranking using pairwise image comparisons. Our GP smoother is described in section III-B and experimental results are included. When compared with commonly used baseline interest estimation algorithms [1], [2], the proposed approach is shown to predict image comparison outcomes with a higher level of accuracy after far fewer comparisons. Section IV shows how image interests can be used for storyboarding, with storyboards quantitatively compared with a state-of-the-art unsupervised storyboarding algorithm [3], by counting the number of objects of interest included in the storyboards. Section V describes the generation of saliency or attention maps, which are qualitatively compared with Itti-Koch saliency maps [4], a widely used saliency estimation approach. Finally, conclusions and recommendations for future work are given in section VI.

II. RELATED WORK

Exploring mobile robots produce a vast amount of information that places a large burden on the human operators responsible for its analysis. A system that automatically flags interesting images or information and presents a summary to an operator is required to remedy this.

Unfortunately, it can be hard to define interesting images, as this is typically context dependent. For example, [5], which investigates the feasibility of classifying images by scientific value to address bandwidth constraints on a Mars rover, shows that domain experts from different fields value and rank images differently.

A. Novelty detection

A common definition of interest relates to novelty, with interest determined by the frequency of occurrence of an event or observation. Novelty detection is often framed as an outlier detection problem. For example, dynamic time
warping has been used to align image feature sequences for a life-logging application, with the alignment quality determining novelty [6]. Here, the authors leverage the fact that people typically experience day-to-day repetition, and assume that areas of mismatch or disagreement with typical daily activity should be flagged as novel.

Neural networks are often used to reason about novelty. For example, Hopfield networks use weights to store information about correlated patterns, with new patterns exciting nodes and increasing the energy of the network. By thresholding this energy, Hopfield networks are able to flag novelty. This approach was used in [7], which showed that a Hopfield network, trained by driving a mobile robot around an environment, was able to detect new objects that were added to the environment after the training phase.

In contrast, [8] use a novelty filter operating on the principle of habituation. Habituation networks recall how frequently they have fired, and become accustomed or habituated to observations the more often they fire. Similar perceptions excite similar regions of the network, and novelty is identified as deviation from the trained model. Self-organising maps have been applied to novelty detection on a sentry robot in [9], with a growing-neural-gas network retraining at set intervals to alter an environment model.

The reconstruction error obtained by using a model of an area’s eigenspace to predict observations is used to detect novelty in [10]. Learning basis functions from video information can be expensive, so the authors restrict the novelty detection to image regions flagged using a saliency measure or feature detector. An incremental principal component analysis (PCA) model of this type has been shown to provide similar performance to a grow-when-required network in an autonomous inspection robot application [11].

If prior information about the environments or observations to be encountered is available, domain-based approaches to novelty detection are particularly effective. Here, classifiers are trained to recognise expected samples, with any misclassification flagged as novel. For example, novel terrain texture is detected using a naive Bayes classifier trained on a number of textures detected previously for an application with a moving whiskered robot in [12]. Person, car and groups of person classifiers are trained for a surveillance application in [13], with classification failures listed as novel. Terrain classification using support vector machines is applied in [14], with negative training data in the form of unlabelled images used to model novelty.

B. Storyboarding video sequences

In contrast to novelty-based image recognition, storyboarding aims to summarise lengthy video sequences using a reduced set of images likely to interest an end-user. This is particularly useful for search and retrieval applications, where users are unwilling to watch a full video in order to evaluate its content. An overview of video storyboarding approaches is provided in [15].

Most storyboarding approaches operate by first segmenting sequences into shots or sub-sequences, and then selecting a representative image for each shot. For example, [16] use a graph-based clustering approach to segment video into static, panoramic, zoom, motion and in-deterministic shots. An attention model trained on a number of low level features is then used to rank the frames in each shot. This approach provided good performance when the informativeness and enjoyability of the keyframes it produced were evaluated by users. Shots are also used in [17], with these segmented by detecting changes in image colour histograms. The authors note that scrolling through images is still tedious, so aggregate keyframes selected from shots to form a new video summary of the type typically available for preview in online video repositories.

MPEG-7 image features have been used in conjunction with image intensity histograms to rank the relevance of images relative to other frames [18]. Video sequence transitions are detected in [19] by tracking image changes, and selecting keyframes most similar to the average of all frames in shots. Shots selected by detecting video frame transition effects may not be well described using a single keyframe, and a statistical run test is used in [20] to segment shots into sub-shots before keyframe selection.

Objects are tracked in image sequences in [21], with images ranked by the length of time objects remain present. A representative frame is selected by finding the frame in each tracked sub-sequence for which the largest number of tracked pixels were present.

Video storyboarding is of particular interest in life-logging applications, where large amounts of data need to be summarised. Here, egocentric cameras are used to record the daily activities of their wearers. Image sequences of this type often have low temporal consistency, as images are not saved constantly due to storage constraints, so change-based shot segmentation approaches tend to fail. An attempt to remedy this is made in [22], which uses an energy minimisation segmentation approach on low level image features to classify images as static, moving camera or in transit. In later work, [3] use a pre-trained convolutional neural network to identify image features for use in event segmentation for egocentric photostreams.

The storyboarding approaches discussed thus far do not necessarily produce keyframes that are likely to be of interest to humans. In an attempt to remedy this, personalised video summaries are produced in [23] by incorporating a prior on the type of information of interest. Here, a natural language request for images is used to retrieve images in a similar category. Gaze fixation clustering was used in [24] to discover areas that are likely to be interesting to humans. Instead of detecting keyframes using novelty, high quality images are found in [25]. Here, a generative model of ‘snaps’ is trained using novelty, high quality images are found in [25]. Here, the attention model trained on a number of low level features is then used to rank the frames in each shot. This approach provided good performance when the informativeness and enjoyability of the keyframes it produced were evaluated by users. Shots are also used in [17], with these segmented by detecting changes in image colour histograms. The authors note that scrolling through images is still tedious, so aggregate keyframes selected from shots to form a new video summary of the type typically available for preview in online video repositories.
Storyboarding tends to occur at an image level, selecting interesting images from a larger set of images. While this may take low level image features into account, it does not provide much information about the novelty of areas of interest within respective images.

C. Saliency detection

Saliency detection refers to the process of finding pronounced features or areas in images and is often related to attention modelling, which aims to determine which image areas humans are drawn to. The Itti-Koch saliency map [4] is probably the most widely used measure of saliency, and relies on flagging multiple low level features in scale space to build a bottom-up model of attention. This saliency map is expanded through the addition of both facial features and scene features to highlight images of potential interest to humans in photo albums in [26]. Although saliency maps aim to flag interesting image areas, they have also been used for image ranking [18]. Salient image regions are extracted using a spectral residual approach in [27]. This approach differs from the Itti-Koch saliency map as it is independent of image features, categories and other prior information.

Contextual information is important for saliency detection, and low-level features are combined with high-level detections like faces together with visual organisation information to extract salient image areas in [28]. These areas were used to build automatic collage models. Feature-based saliency models may not always agree with human definitions of saliency. An attempt to remedy this is made in [29], which trains an attention model using a number of hand selected image features by recording human gaze. A support vector machine is able to classify the potential interest value of an image area using this model.

Object recognition is used to build semantic maps of environments in [30], with saliency maps used to flag potential object locations. Salient keyframes have been used to improve loop closure to boost mobile robot mapping performance in [31]. Here, the authors balanced exploration and loop closure, preferring paths with high saliency levels.

D. Interest detection using pairwise ranking systems

The subjective and contextual nature of image interest makes it hard to design a bottom up interest detection algorithm. Instead, a far more sensible approach would make use of operator supervision to learn interest. Relative image comparisons are an intuitive way to infer user preference [32], and frequently used for image ranking because they can provide more stable and useful rankings than individual image-based scoring systems [33].

A number of effective ranking algorithms have been developed for ranking using pairwise comparisons. Ranking systems such as the Elo chess rating system [34] and TrueSkill™ [1], a Bayesian ranking scheme extension to Elo, account for relative player skills and performance inconsistency.

TrueSkill™ is ubiquitous in image ranking systems [32], [35], [36], [37], [38], [2], providing an effective approach to estimating image interest for a wide range of applications. For example, Hipster wars [33] uses TrueSkill™ to train an image-based style classifier in a fashion application from style judgements, using a part-based model to generate saliency maps that associate clothing items with styles.

III. IMAGE INTEREST ESTIMATION

The proposed approach to mobile robot storyboarding uses pairwise image comparisons to predict image interest. Initially, a baseline Bayesian ranking scheme is used to estimate image interest scores. This is combined with a Gaussian process smoother that improves estimates by incorporating image similarity information from convolutional neural network image features.

A. Probabilistic image ranking

This work uses the TrueSkill™ Bayesian ranking scheme [1] to compute image interest scores. TrueSkill™ is a probabilistic ranking system that assumes players in a game have respective skills, \( w_1 \) and \( w_2 \), and that game outcomes can be predicted by the performance difference between skills, subject to Gaussian noise effects.

For image pairs,

\[
t \sim N(s, 1)
\]  

(1)

models the interest difference between two images, with \( s = w_1 - w_2 \) the interest difference and the standard normal distribution accounting for potential labelling errors [2]. Comparison outcomes are given by \( y = \text{sign}(t) \), with a positive \( y \) indicating a win for image 1, and a negative \( y \) indicating a loss.

Interest estimation under this model can be treated as a Bayesian inference problem, with the posterior over skills described by

\[
p(w_1, w_2 | y) = \frac{p(w_1)p(w_2)p(y | w_1, w_2)}{\int \int p(w_1)p(w_2)p(y | w_1, w_2)dw_1dw_2},
\]  

(2)

where \( p(w_i) = N(\mu_i, \sigma_i^2) \) is a Gaussian prior over image interests and

\[
p(y | w_1, w_2) = \int \int p(y | t)p(t | s)p(s | w_1, w_2)dsdt
\]  

(3)

the likelihood of a game outcome given interests. The model above is easily extended to multiple images, \( w \), by chaining comparisons, \( y \), together in a large graph, producing the posterior

\[
p(w | y) \sim N(w_m, \Sigma_n),
\]  

(4)

with mean \( w_m \) and variance \( \Sigma_n \). Equation (4) is an intractable posterior, but can be estimated numerically [39].

B. Gaussian process interest refinement

Image ranking using TrueSkill™ is effective, but requires that a large number of pairwise comparisons be made, a potentially time consuming and laborious process. In an attempt to remedy this, [2] introduced a smoothing algorithm that used the temporal image interest similarity present in video to improve interest estimates. This approach relies on a Markovian assumption, and so fails to account for interest
Prediction accuracy refers to the fraction of game outcomes that were correctly predicted by computing the differences between predicted image interests and the ground-truth interests. The accuracy for each algorithm is shown in Figure 2.

The proposed approach to image interest estimation was tested on a dataset of 4000 outdoor images captured by an autonomous rover. 15000 baseline pairwise image comparison results, $G_{\text{baseline}}$, were obtained by presenting randomly selected pairs of images to a robot operator and asking which image was more useful to them. In general, the robot operator (wary of potential collisions) favoured images that contained cars or pedestrians. The 15000 baseline image comparisons were split into test, $G_{\text{test}}$, and training, $G_{\text{train}}$, sets, comprising 5000 and 10000 comparisons respectively.

Three interest detection algorithms were compared: A TrueSkill™ interest estimate (TS) [1], a temporally smoothed interest algorithm (TTS) [2], and the proposed GP interest estimation approach, hereafter referred to as GP-CNN.

GP-CNN uses image features extracted from a convolutional neural network, pre-trained for image classification on the ImageNet database [41]. Figure 2 shows a trace of the image comparison prediction accuracy for each algorithm. Here, an increasing number of comparisons sampled from training set, $G_{\text{train}}$, were used to predict game outcomes for the comparison pairs in $G_{\text{test}}$. Prediction accuracy refers to the fraction of game outcomes that were correctly predicted by computing the differences in predicted image interests.

It is clear that GP-CNN outperforms the interest estimation of [2] and [1]. Smoothing in image feature space requires attributes selected for smoothing. The image attributes considered here comprise 2048 image features extracted using a pre-trained convolutional neural network [41], while the cosine similarity is used as the distance measure. The length scale $l = 1.0$ is chosen to be constant for computational simplicity, but could also be inferred as part of the GP regression process.

The GP kernel introduces behaviour that can be considered analogous to a soft loop closure [42], but with images containing similar content allowed to share interest information, regardless of image capture position.

C. Experimental results

Fig. 2. Traces of the image comparison prediction accuracy highlight the performance of GP-CNN.
only 1927 training comparisons to outperform a baseline TS algorithm trained with 10000 training comparisons. When the full 10000 training samples are used to estimate image interest, GP-CNN correctly predicts game outcomes with 82.9% accuracy.

Figure 3 shows the posterior predictions for GP-CNN when all 15000 comparisons are used for interest estimation, along with a selection of images corresponding to various interest levels. Images with higher interest scores contain objects of interest (pedestrians or vehicles, while images with lower interest scores are more likely to be empty road scenes.

### IV. Storyboarding

The image interest estimates obtained using GP-CNN are easily used for storyboarding. This is a simple matter of selecting $N$ images corresponding to the top image scores, requiring that these are at least $d$ images apart. Figure 4 shows a 24-image storyboard summary of the autonomous rover data set.

This storyboard contains images likely to be of interest to a robot operator. In contrast, most commonly used storyboarding schemes lack the user-driven context of the proposed interest-based approach. This can be seen in Figure 5, which shows a 24-image storyboard produced using hierarchical agglomerative clustering [43] on the same pre-trained convolutional neural network image features used by GP-CNN. This approach [3] produces a diverse set of images, as the clustering rewards image dissimilarity, but many of the images produced are not of interest to an end user.

### V. Saliency Detection Using Image Interest

It is clear that user-driven interest estimation can be used to identify images of interest to a mobile robot operator. Section III-C showed how the GP-CNN approach to interest estimation dramatically reduced the number of comparisons required for interest estimation. However, this approach has an additional benefit, in that it allows for interest-driven image saliency maps to be obtained using standard neural network visualisation tools.

Figure 6 shows a saliency map produced using the blanking approach described in [44] on our interest model. Here, the change in algorithm output is observed as a sliding window blanking out image parts is moved over an image. A negative change in output indicates that the blanked image area contained elements of importance. For our interest estimation approach, a positive change in interest indicates that a blanked area did not contain anything of interest to an operator, while a negative change in interest output indicates that the blanked area contributed greatly to the original interest score. The image overlays in figure 6 were created.
Fig. 4. Interest-based storyboarding is user-driven, producing images likely to be of interest to an end-user. Here, all 24 images contain a pedestrian or vehicle.

Fig. 5. Clustering approaches to storyboarding [3] produce visually appealing boards with a large variety of images, but these may not be useful to a robot operator, as these algorithms are unsupervised and fail to account for user interest. As a result, only 15 of the 24 images contain a pedestrian or vehicle.

Fig. 6. The proposed approach to image interest estimation allows the creation of user-driven saliency maps. Red image area overlays indicate a region of interest to an end user, while blue image area overlays are of less interest. The top row of attention maps were produced using GP-CNN, while the bottom row shows Itti-Koch [4] saliency.

It is clear that the GP-CNN approach has learned that the operator is interested in vehicles and pedestrians. This behaviour is particularly useful, as it allows images of interest to be presented to robot operators with regions of interest flagged directly therein. The Itti-Koch approach is effective, providing more fine-grained saliency, but tends to highlight unwanted image components because it lacks the contextual information gained from the pairwise comparisons. Finer-grain saliency detail could be obtained using GP-CNN by passing different window sizes over the image, but this can become computationally expensive.

Figure 7 shows a 64-image storyboard with attention map overlays. The proposed approach is effective at highlighting smaller objects in the images, but struggles with larger areas of interest. This can be attributed to the nature of the features extracted by the pre-trained neural network and the size of the blanking region.
VI. CONCLUSIONS AND FUTURE WORK

This paper has introduced a user-driven interest detection algorithm for mobile robots. Unlike existing unsupervised storyboarding algorithms, the proposed approach allows for the direct inclusion of user of operator requirements, through a rapid and intuitive training process. Here, an operator is presented with random image pairs, and asked to select images of greater interest for their application. Standard probabilistic ranking algorithms using pairwise comparisons like these typically require a large number of comparisons, but our Gaussian process smoother dramatically reduces this number, by making use of similarities between image features extracted using a pre-trained convolutional neural network.

A particularly useful by-product of this approach is that saliency or attention maps, customised for user interest, can also be generated. This is particularly useful for inspection robots, which could use the proposed approach to automatically identify images of interest, along with image areas of concern. This could allow for active robot navigation strategies that leverage this information, thereby resulting in improved inspection information.

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