Activity Identification and Visualization[1]

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Abstract. Understanding activity from observing the motion of agents is simple for people to do, yet the procedure is difficult to codify. It is impossible to enumerate all possible motion patterns which could occur, or to dictate the explicit behavioural meaning of each motion. We develop visualization tools to assist a human user in labelling detected behaviours and identifying useful attributes. We also apply machine learning to the classification of motion into motion and behavioural labels. Issues include feature selection and classifier performance.

1 Introduction

Surveillance observations are becoming increasingly available, meaning the ability to continuously watch an area for long periods of time with multiple sensors. The types of analysis required for today's military (such as counter-terrorism) and commercial security applications increasingly involve interpreting observations made over time. The amount of data that is available is overwhelming the abilities of human analysts to exploit it all. Therefore, tools are needed to assist the analyst in focusing in on portions of the data that contain activities of interest. For example, a tool could alert the analyst to the presence of an activity of known interest, or an unusual activity.

The problem is unstructured, in the sense that there may be a great variety of objects and actors in the scene, and the types of activities that occur may not be known in advance. Sometimes the activity of interest will be buried within a background of other unrelated activities. It could be very difficult to develop purely automated tools to solve the problem. Therefore, our approach is to develop interactive tools to help users to understand the activities in a scene. For example, visualization tools allow the user to see patterns in the surveillance data, and choose appropriate features for pattern recognition algorithms.

In this work, we focus on pure motion track data, which is simply the location of actors (people or vehicles) as a function of time. We do not assume the presence of

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any detailed information about the actors, such as their identity, shape, what they are carrying, etc. Such pure motion data is typical of what would be available from remote sensors that monitor large areas or facilities.

Our focus on analyzing and understanding large numbers of motion tracks, using visualization and data mining, is novel and not directly addressed by previous work. A related project is the VSAM project at CMU (1997-2000), with support from DARPA and RCA, which developed automated methods of video monitoring in urban and battlefield scenes. The focus of that effort (in the 1990's) was to employ computer vision to identify small numbers of objects and understand their activities in real-time.

Madabhushi and Aggarwal [1] showed how Bayesian inference could be used to classify human activities, based on posture and position (not based on the motion in a scene). There is a significant literature on modelling and classifying human activities based on positional information that can be gained from videos (e.g., [2-5]). Similar work on video surveillance has results related to understanding human activity. Unfortunately none of this work emphasizes the use of computer visualization tools to enable humans to participate in the classification of complex activities.

On the other hand, data visualization has been used extensively, either by itself, or in combination with machine learning, to improve the understanding of large data sets. This has been useful in intrusion detection for computer networks, and in using anomaly detection to detect fraudulent transactions or insurance fraud (see for example [6]). Another focus of data mining with visual tools is the identification of patterns in time-sequences of data, such as in understanding the sequences of actions taken by visitors to Web sites (see for example [7]). These results were not applied to human activity classification.

The rest of this paper is organized as follows. Section 2 describes the data that we worked with and how we collected it. Section 3 describes the visualization tools that were developed. Section 4 describes our approach for detecting anomalous tracks and scenes. Section 5 describes our approach and results on classifying distinct activities based on motion as well as behaviour. Section 6 provides conclusions.

2 Data Collection and Processing

The domain we used for data collection was the visual observation of students on campus. We placed a camera on top of buildings around campus, and recorded video of students walking between buildings and performing other activities. An example street intersection scene is shown in Figure 1. Other scenes included:

- ˜ Pedestrian scenes: People walking through a plaza or across a field.
- ˜ Flyers: A person handing out flyers to people on a street corner or plaza.
- ˜ Sports: soccer, volleyball, Ultimate Frisbee

We used a digital (Hi-8) camcorder, and then transferred the video to a computer in the form of an AVI movie file. Progressive scan mode was used. We then converted the AVI movie into a sequence of still images. The images were 640x480x8 pixels (grayscale), and were taken at 30 frames per second.

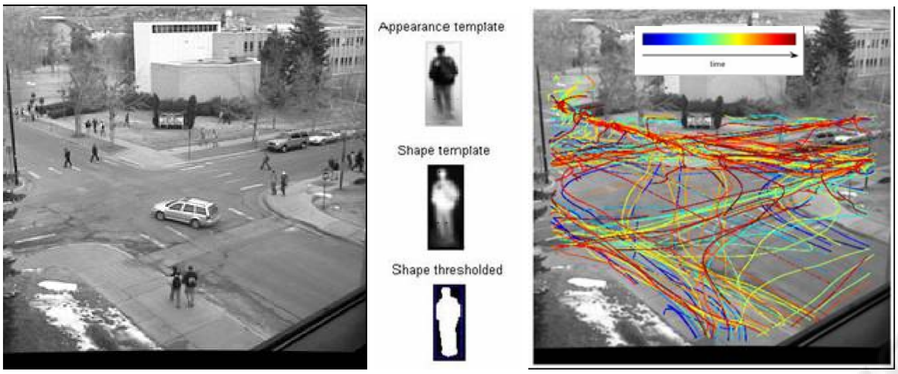


Fig. 1. Data collection and processing. (Left) Street intersection scene. (Center) The tracker maintains templates of the shape and appearance of each object being tracked. (Right) Tracks from street intersection scene

An automatic tracker program was developed to automatically track all moving objects in the scene and write their coordinates to a track file. First, a background, or “reference” image was obtained by averaging all the images. Because moving objects tend to pass quickly in front of the background, they tend to average out.

The operation of the tracker was as follows:

1. Read in the next image of the sequence.
2. Take the difference between this image and the reference image. Threshold the difference image and find connected components.
3. For each component that is not already being tracked from previous images, start a new track. The track file information consists of the location of the object, its “bounding box” in the image, and an “appearance template” of the object within the bounding box. A “shape template” is also computed, which when thresholded is a binary image of the silhouette of the object (Figure 1, center).
4. For each tracked object, perform a cross correlation operation to find the most likely location of the template in the new image. Then update the template image of the object by computing a running average of its image.

For the street scene, Figure 1 (right) shows all tracks obtained after 3 minutes. The actual world coordinates were also computed, using the assumption of a flat world. Very short tracks (less than 3 seconds) were discarded, because they were considered to be due to noise. The (x,y) locations of the remaining tracks were smoothed by running a low pass (Gaussian) filter, with σ = 0.4 seconds.

3 Visualization Tools

After tracks have been detected and measured, we perform the following steps:

1. Visualization/analysis of the results of motion tracking
2. Derivation of additional numerical attributes of motion tracks
3. Visualization of derived attributes

4. Classification of tracks and scenes

Data visualization is an important component of the process. Two visualization tools, a track visualizer and an attribute visualizer, are described below. We used the track visualizer to determine the accuracy of the track detection, which also provided us with an improved understanding of the characteristics of the data that need to be analyzed. This understanding led us to propose various numerical attributes of the tracks that could be used to differentiate between different human activities. The visualization of these attributes enabled us to formulate several different approaches to classifying the tracks, and to validate or invalidate these approaches.

The track visualizer presents the motion tracks in a scene as a set of line segments in the plane where they were detected (Figure 2, left). The motion can be animated by translating symbols (e.g. colored cubes) along the tracks, illustrating the object's position over time. The video frames (from which the motion was detected) can be replayed as an animated background. The user can match the detected motion tracks with the moving objects in the video, and can spot discrepancies in the track detection. The track visualization provides 3-D scene navigation, so that the user can see the motion tracks from any direction. A background image of the scene is displayed behind the tracks so that the user sees the tracks in the perspective of the simulated physical position in the scene. The motion tracks and segments within the tracks can be labeled, based on automatic or manual classification of the tracks. Colors are applied to the tracks indicating the associated labels.

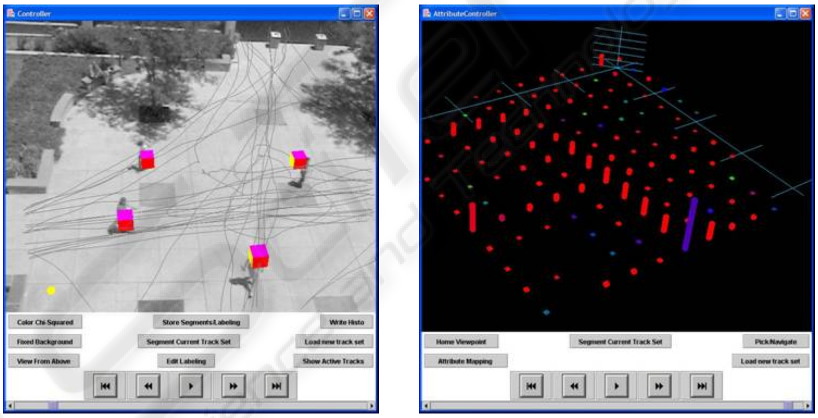


Fig. 2. Visualization tools. (Left) Motion tracks superimposed over the corresponding video image. (Right) The attribute visualizer allows a general mapping of track attributes to scene dimensions - this shows the distribution of starting(x,y) positions for actors in a scene

The attribute visualizer provides a 3-D animated display of numerical attributes associated with motion tracks or with segments within motion tracks. In this context, an "attribute" is any (discrete or continuous) function that can be calculated from the data associated with a motion track. Attributes to be plotted are specified as functions of track segments, and can depend on any computed property of the track segment, such as ground coordinates, speed, or orientation. The attributes can be defined by

Java routines (previously defined, then invoked at runtime) or calculated externally, using, for example, MatLab™, to interactively calculate the values of the attribute from the data associated with each track segment. The values of track attributes are mapped at run time to any of a number of plotted dimensions, including x, y, and z coordinates, time (i.e. animation frame number), color (hue, saturation and value), transparency, symbol size, and symbol shape. The resulting animated graphs can be compared to evaluate differences between numerical measures associated with the scenes and with actors in the scenes. Histograms of track attributes are particularly useful.

In Figure 2 (right) we show the visualization of some numerical properties of a scene. The histogram indicates the frequency of starting x,y coordinates for tracks in a scene. The histogram bars are color-coded according to the average turning angle of the corresponding track segments.

4 Anomaly Detection

In this section, we describe our method for detecting anomalous activities based on probability distributions. We can characterize scenes, and actors within these scenes, by comparing the distributions of speed and turning angle for the actors in the scene. The distributions are approximated by calculating histograms of these attributes. Each actor is associated with a motion track, consisting of the actor's position at 1/30th second intervals.

An average speed can be calculated between any pair of positions and times, evaluated as distance divided by time. The turning angle is a number between -180 and 180 (degrees) determined from three successive positions on a motion track (and the resulting direction angle change) separated by a specified time interval.

Given any scene, or a single actor within a scene, and for each time interval, there is associated a histogram (approximating a probability distribution) describing the distribution of speeds and turning angles in that scene, by one or all of the actors in the scene. In the experiments we describe here, we chose a logarithmic sequence of time scales, e.g. 1, 2, 4, 8, …, frames and calculated the histograms for each time scale.

To compare actors or scenes, we used the chi-squared statistic as measure of the similarity between two histograms. The chi-squared statistic is associated with two binned variables, and can be used to compare the histograms associated with different scenes, as well as the histograms associated with actors within these scenes [8]:

$$\chi^2(R,S) = \sum_i \left(R_i\sqrt{S/R} - S_i\sqrt{R/S}\right)^2 \Big/ \left(R_i + S_i\right) \qquad \textbf{(1)}$$

where $R = \sum_i R_i$ and $S = \sum_i S_i$.

The computed chi-square statistic is used to test the null hypothesis that two distributions are the same. A relatively large value indicates that the two are not identical (i.e., we reject the null hypothesis). We applied this statistic to distinguish one type of sports scene from another, and the result is shown in Figure 3.

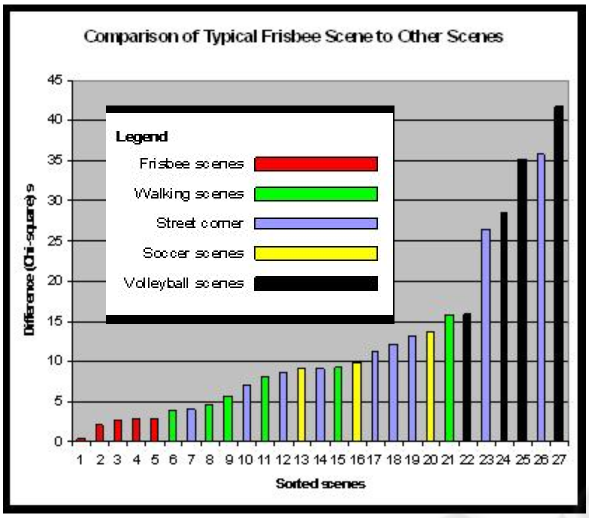


Fig. 3. A comparison of different scenes using the χ^2-statistic, applied to the histograms of turning angles and speeds. The plotted value is determined by applying equation (1) at each scale, and then averaging these values of χ^2

Note the small values of χ^2 resulting from pairs of different “Ultimate Frisbee” scenes, meaning that these scenes are similar to each other. On the other hand, the χ^2 value is larger when comparing the “Frisbee” scene to other unrelated activities such as volleyball or walking through the street corner. This difference between histograms is due to the fact that Frisbee players have typically much more high-speed and high-turning intervals than actors in the other scenes.

Similarly, the χ^2 statistic was also applied to identify “unusual” activities within scenes. Using equation (1), the histogram associated with each actor’s motion track is compared with the histogram of all other actors in the scene (not including that actor). In this case the method correctly identified the distributor of flyers as the most “unusual” actor in the street scenes. This is likely due to the fact that the track for the flyer distributor tends to meander, while the other actors tend to go straight through the scene.

Thus, our method can detect unusual activities and scenes in an unsupervised manner. The human supervisor can then inspect these unusual events and, if they are of interest, label them. The system can then learn to recognize these activities using machine learning methods, as is described in the next section.

5 Activity Classification

In this section, we describe our method for classifying activities using supervised machine learning methods. Activity classifications can be proposed in an unsupervised manner as discussed in the previous section, or provided directly by a human user. The human-generated labels impose added complexity, as a person often resorts to arbitrary boundaries between activity labels. The added complexity of human-based class labels provides a more realistic example of our target application. We examine two types of classification, namely motion-based and behaviour-based classifications. Motion-based classifications are strongly tied to attributes such as velocity or acceleration. Behaviour-based classifications are determined by a human user from examining the context in which the activity occurs. These represent a much more difficult set of classifications, as the feature set utilized does not take into account full contextual information.

We first divide tracks into equal length segments of approximately three seconds in duration. (In a pilot study, we found through cross-validation that this segment length provides a good balance between expressiveness of a segment and the number of segments available for training.)

5.1 Feature Selection

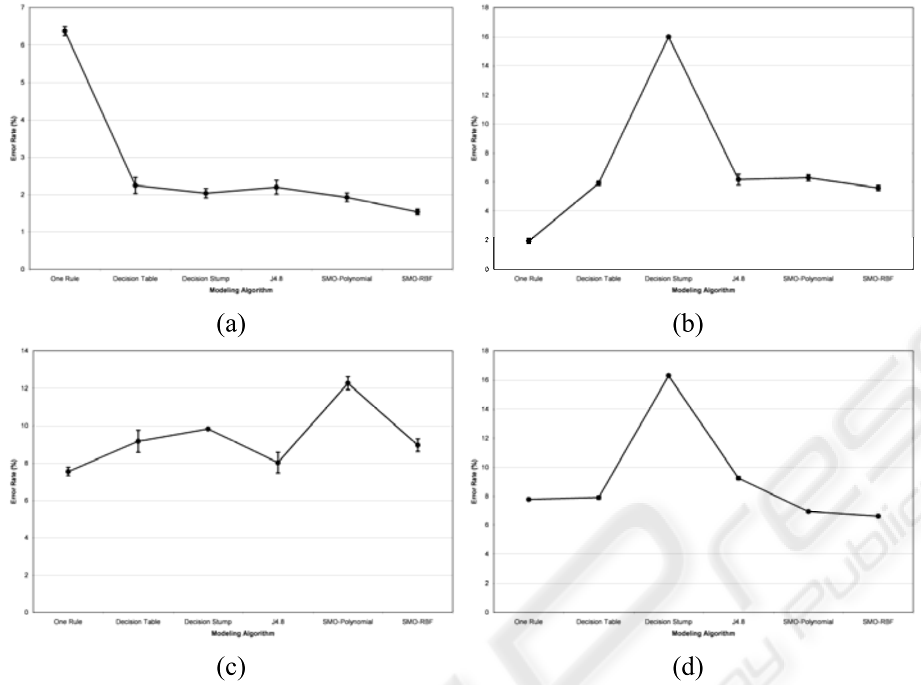
We discarded absolute positional data because the position at which a behaviour occurs is usually irrelevant in terms of describing the behaviour. Instead, we used velocity, acceleration, speed, and turning rate computed at every position of a given activity segment. Velocity and acceleration are vector quantities, and are computed at each point of a track segment by use of the first and second forward difference, respectively. The speed is the magnitude of its velocity, and the turning rate is the difference in angle between the velocity vector at time t and t+1. Finally, we compute the minimum, maximum, and average speed and turning rate over the activity segment.

5.2 Motion Classifications

The first set of classifications we consider are motion based, meaning that the metric is primarily based on overall speed of the segment. For the flyer scenes, an individual distributes flyers to other individuals travelling through the area. The flyer person meanders about the scene, occasionally intercepting others. The first motion classification experiment matches a given activity segment to the label of “meandering” or “normal” activity. A meander activity is loosely defined as any activity segment where the individual is stopped completely, or is moving slowly in an indirect path.

To evaluate performance of machine learning classifiers, we perform ten times ten-fold cross validation on a set of six classifiers. Two of these were “simple” classifiers with high bias and low variance: (1) one-rule and (2) decision stumps. The others were more “complex” classifiers: (3) decision tables (low bias, high variance), (4) decision trees (low bias, high variance), (5) SVMs with Polynomial Kernel of power 2 (medium bias, medium variance), and (6) SVMs with Gaussian RBF Kernel of σ = 0.01 and regularization constant C=1000 (low bias, medium variance).

Model performance appears in Figure 5a. The majority of the models perform at around 2% error. The SVM with RBF model has the best performance. All models perform well on the activity segments except for the “one rule” model. This preliminary data set shows that our activity segmenting and modelling process performs well.



(a) (b)

(c) (d)

Fig. 4. (a) Performance on flyer scene, “meander” vs. “normal”. With the exception of the one rule model, all of the modelling algorithms perform well on classifications based on motion. (b) Flyer scene, multiple speed labels and cars. One rule outperforms all other classes with a set of thresholds based on average speed. (c) Performance on sports scene, motion classification (standing, walking, and running). (d) Performance on flyer scene, flyer behaviour vs. other behaviours. Classification labels are assigned by the activity of the individuals in the scene. One of the individuals in the scene is distributing flyers to others who pass through the scene. As the nature of the flyer person’s behaviour is different, their motion track has different properties

The second motion classification experiment is also based on the flyer scene. It moves to a higher number of activities being distinguished. These are stopped, slow, and normal-paced human motion, as well as all cars and bicycles grouped separately. A speed-based threshold approach performs equally well here, as all that is necessary is an additional threshold to differentiate slow activities from stopped activities. With this experiment, we add in more of a behavioural classification in the car label, as stopped and slow car activities are not extracted from the overall car motion track.

Model performance appears in Figure 5b. Most models perform around 6% error. Decision stumps perform extremely poorly, due to its selection of a single attribute, and a single threshold; it cannot represent more than two classes. One rule out performs all others by far. As initial labelling of the activities was performed by a human user, the differences between what constitutes a slow activity versus a stopped or normal-paced activity is not a hard threshold, though the threshold approach of one rule performs well. As for the cars and bicycles, a concern was that their activity signature would be too easily confused with a person, as the vehicles stop and move slowly through the intersection. On the contrary, the majority of the cars and bicycles are correctly classified. We attribute this in large part to the segment length selection, where the greatest segment length possible is selected.

The third motion classification experiment switches to the sports scenes. Class labels distinguish the basic motion pattern of a player between standing, walking, or running. Added complexity arises due to the human-based class labels, as the dividing thresholds between class labels is arbitrarily enforced by the person generating the labels. There is likely a shift in class thresholds not only within sports, but across sports as well. For example, a person who is labelled as walking in a soccer game might be labelled as standing in a volleyball game, simply because of the context in which the motion takes place. The added complexity of human-based class labels provides a more realistic example of our target application.

Performance is reported in Figure 5c. As with the second motion experiment on the flyer scene, decision stumps perform poorly due to the bias against decisions involving more than two classes. Other than the decision stump model, the remaining models perform between 6.6% and 9.3%. The best of these are the SVMs; the worst is the decision tree. Performance is slightly poorer than with the second motion experiment. The boundary between the activities was again allowed to be arbitrarily defined by the human user performing the activity labelling. This may be part of the impact on the performance.

For motion-based classifications, performance on all scenes is on average less than 10 % error rate. Our segmentation and feature selection process works well at modelling motion-based classifications.

5.3 Behavioural Classifications

Behaviours are much more difficult to express explicitly than motion-based classes, as a single threshold cannot encapsulate all the variation which exists in a behaviour. In generating a behavioural label, e.g., a Frisbee player or a flyer person, often an entire motion track is placed in a behavioural class. This is not to preclude the possibility of an individual exhibiting multiple behaviours over the duration of their motion track; rather, it is a result of the scenes which generate our motion data. We have no occurrences of a travelling person stopping to distribute flyers, or of a soccer player becoming a Frisbee player.

Our experiment classifies the flyer person versus all other individuals in the scene. One might expect this problem to be very straightforward, as the behaviour of the flyer person is distinct from other actors in the scene. On the other hand, there are times when the flyer person exhibits behaviour which is similar to normal traffic, as well as times when the travelling individuals stop or move slowly.

The flyer person has a signature which tends to meander about the scene, occasionally moving to intercept others, and occasionally stopping to wait. Other individuals tend to travel at a constant pace through the scene, though at times they slow or stop. Each track is labelled as either a normal behaviour or a flyer person behaviour. Modelling results are displayed in Figure 5d. The difference among modelling algorithm performances is slightly more spread out. The range is from about 7.5% to 12.5% error. The best models are produced by one rule and decision tree. The worst modelling algorithm at this task was the SVM constructed with the polynomial kernel. In general, overall modelling performance is promising. The modelling techniques were able to represent the ill-defined activities fairly well.

6 Conclusions

The results of the various experiments provide insight into the potential for behavioral classification of motion tracks. In the motion-based classifications, a simple metric was selected based loosely on the average speed of the individuals being monitored. Specific thresholds separating the activities could have been used, but the arbitrary assignment of categories by a human user requires more flexibility from the modeling tools. These experiments stand as the preliminary proof of concept that such classifications on motion tracks are attainable.

The behavioral classification experiment consists of an abstract label being assigned with no regard for which of the available features might best help distinguish between class labels. In the flyer scenes, the flyer person tended to move in a different pattern than other travelers. This was sufficient to recognize the activity in cross-validation experiments.

Preliminary work indicates that there is potential for improvement in modeling behavioral data by the inclusion of windowing data. The improvement arises from an extension of the information available where track length exceeds segment length. The overall performance of our approach to motion and behavior classification is a success.

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