Face detection using Automatic Bootstrapping technique

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***Abstract*— Face recognition is performed with the help of extracted Segment of a continuous video signal. The process is based on a motion based bootstrapping algorithm concurrent to a shape based active contour. The shape-based active contour uses finite shape memory that is automatically and continuously built from both the bootstrap process and the active-contour object tracker. The bootstrapping stage provides important motion and shape information to the object tracker. A scheme is proposed to ensure that the finite shape memory is continuously updated but forgets unnecessary information. Two new ways of automatically extracting shape information from image data given a region of interest are also proposed. This information is found to be essential for fully automatic initialization of the active contour. By using the human gaits model obtained from the source, the output of the object tracker is further given to the memory and compared with the pre-stored data to enable the system to detect whether the input data matches with the pre-stored data and provide access. Hence it could work as an effective access control mechanism.**

I. Introduction

OBJECT contour tracking is a complicated process due to many factors, including variations in object appearance and deformations of object shape, e.g., for articulated objects or changing perspectives of 3-D objects. Therefore, object tracking approaches need to incorporate some form of shape modeling to enable successful contour localization and tracking.

An ideal medium for shape modeling is the active contour model, which has been extensively investigated in conjunction with prior shape knowledge since at least [1] and [2].These spline-based approaches are limited by topological constraints unlike level-set-based active-contour approaches, e.g., in [3]. Principal component analysis (PCA) is often used in these techniques to compress and summarize the important components of a set of characteristic level sets [3], [4] or control points modeled using an active shape model (ASM) [5]. These techniques use a set of representative 2-D contours of an object, which is learned *a priori* to enable more accurate contour localization in object segmentation or object tracking techniques.

Many prior shape-based tracking methods have been demonstrated to be quite robust, providing accurate outlines of the shape of the object being tracked. For example, Cremers [6] used a dynamical shape prior to enable tracking under high-noise conditions where the prior shape information was combined with a second-order autoregressive model of the transformation of the shapes of a person walking. Dambreville *et al.* [7] demonstrated the inability of a linear PCA shape space to fully describe the nonlinear deformations prevalent in deformable or articulated objects in static images and video data. The authors therefore chose to embed their shape prior in kernel space using kernel PCA and presented impressive segmentation and tracking results.

However, preparation of extensive prior shape knowledge is not always convenient and even cumbersome. Furthermore, many methods can encounter difficulties if the tracked object is protean and cannot be easily approximated by the current reduced dimensional shape space.

Recently, Fussenegger *et al.* [10] described an approach that was able to update a reduced dimensional shape space online using robust incremental PCA [11]. Such methods are still dependent on manual extraction of relevant information about the objects to be tracked, requiring at least a manual segmentation of the object in an initial frame. In addition, while using a fixed-shape-prior-learned *a priori* provides a distinct advantage of making the object tracking process more robust, a dynamically learned prior can result in the active-contour model becoming more dependent on the manual adjustment of parameter values [12].

Online learning is not limited to shape-based techniques. Nummiaro *et al.* [13] used online learning for tracking and learning of a color distribution of the tracked object.

Tu *et al.* [14] also used an appearance-based model where a number of key frames were manually provided to help constrain the tracking system enabling head pose tracking. Online updating of the histogram information was used for individual frames, but new observations were not combined for future head pose tracking. Again, shape information was not included in the model formulation where the histograms for the mean-shift tracking were computed in a rectangular region of the image space.

Pan and Schonfeld [15] investigated the use of higher order particle filters to provide improved motion estimates obtained from a tracking system using an adaptive block-matching technique. Earlier variations of their tracking system included an active contour to adapt the tracked ellipse to the relatively static shape of the human head for individual frames in [16].

Gai and Stevenson [17] used robust appearance modeling in a tracking framework with the use of a student's distribution version of PCA but without modeling shape information. The authors compared their work with that in [18], which was described as robust because of the use of an incremental PCA approach for (online) learning the appearance of the tracked object. However, the PCA subspace used by Ross *et al.* did not explicitly include a step or modeling to assist in the automatic rejection of outliers. In contrast to this, De La Torre and Black [19] described a robust approach to subspace learning using robust M-estimation. Their work was found to be computationally more demanding but equivalent in power to the work by Skocaj *et al.* [11]; a variant of which was later used by Fussenegger *et al.* [10] in their online adaptive active-contour framework.

A number of authors have combined feature tracking with object shape or contour tracking. Feature tracking helps to improve the performance of the process of object tracking and is relatively robust even if the object undergoes significant changes in shape or photometric properties, e.g., due to changing light conditions. Furthermore, shape information, such as an active contour combined with feature tracking, enables an object tracking approach to provide additional information to the tracking system. This may include new unseen shape information and further regional information such as the distribution of the colors of the object.

Smith and Brady [20] proposed an approach based on feature tracking combined with hulls attracted to edge strength. The technique provided a way of extracting the tracked object shape in the form of a radial map enveloped around clustered motion features. This limited shape information could be enhanced with the use of edges from an optional edge detector. McCane [21] described an approach that imposed constraints on the motion of features dependent on immediate neighbors connected by an edge in a minimum spanning tree (MST), which was also used

Gouet and Lameyre [22] used corner-feature tracking in combination with an active contour. Features were tracked using interframe spatial appearance matching rather than optical flow (i.e., similar to [20] and [21]), primarily to overcome problems associated with tracking through occlusions. An active contour was then defined around the envelope of the tracked features. The system required manual initialization for the first frame. Olszewska *et al.* [23] utilized an ASM on a set of corner features. The ASM was used to track objects, which in turn identified suitable bounds for corner points in each new frame unless an occlusion had been detected. As for [22], the ASM required manual initialization before tracking could commence.

Most of these techniques assume accurate corner identification and tracking, unlike that in [21], which indirectly checks the consistency of tracked features across frames via the edges connecting neighboring features. Gouet and Lameyre [22] describe an approach that somewhat mitigates inaccurate corner tracking by assigning high confidence to corner points within the converged active-contour region. Unfortunately, this does assume that the active contour can converge to a suitable minima without the use of a shape prior, which is often not possible when the video data consists of complex photometric information in the foreground or background.

A. contour-based shape learning

This paper proposes an online active-contour-based shape learning model, which is fully automatic. Unlike our previous work [12], the system applies an original automated bootstrapping stage, and it is further combined with a novel multilevel approach to feature, region, and object tracking. The system also proposes a finite-sized shape memory, which automatically eliminates unnecessary shape information.

Overall, the proposed framework tackles a number of important and unsolved issues in shape-based object tracking, i.e., bootstrapping and online learning of an object's changing shape.

B. concept Organization

The next section presents the proposed methodology. Section II-A describes the feature tracking, clustering, and higher level region-based tracking technique. Section II-B describes how shape information is automatically extracted from the tracked regions. Sections II-C and II-D describe the initialization and updating of the object shape memory. Section II-E describes the shape-based active contour, and Section II-F provides an algorithmic overview of the entire system. Section III presents results and discussion.

II. Proposed Work in Tracking

There are two main components of the proposed tracking framework, as shown in Fig. 1: a bootstrapper stage, which is a motion-based sparse-in-time shape and region tracker, and an active-contour stage that tracks shapes,which is guided by the output of the bootstrap stage. The object shape is bootstrapped here by assuming that, for at least a subset of the frames, the object will possess some form of differential photometric properties from the region immediately surrounding the object. Two alternative approaches are described that bootstrap this information purely from crude regional information: one operating over each object region as a whole and the other performing a local differential analysis. Shapes that are extracted using these processes are then analyzed for consistency across individual frames using a shape overlap metric. Consistent shapes are then stored in an associative memory for tracking by the shape-based active-contour tracking framework. The similarity of learned shape information over time can be observed in similarity weight matrices of the contents of the memory. Shapes that are similar to previously observed shapes can be forgotten.

Following the bootstrapper stage is an object tracking stage that consists of a shape-based active-contour object tracker. The bootstrapper stage provides an initial memory from which the object tracker can perform a more detailed analysis of the data and infer the tracked object shape. The object tracker for each new frame provides a new object shape that can be included in the shape memory. The shape memory is then used to infer future object shapes. Some shapes in the shape memory will not be used very often, and shapes that have been used rarely are automatically removed. This means that the shape memory remains finite and that any future observations of shapes will be compared with shapes that have already been found to be useful. This results in more efficient shape memory usage and relatively stable shape memory where the integrity of the memory is more likely to remain intact for a longer (indefinite) period because irrelevant or badly extracted object shapes are more likely to be forgotten before first use so that the tracked shape is not adversely affected. The robustness of the active-contour framework is enhanced further with the use of the alpha shapes as an initial prior for each individual frame to guide the tracking process and to reduce the likelihood of the propagation of errors in the object contour tracking process. Furthermore, the proposed method is not exclusively for video acquired using a stationary camera as no such explicit assumption (e.g., background subtraction) is used in the development of the system.

A. Feature Tracking, Clustering, and Region Tracking

Potential foreground features are identified based on non-membership of the dominant background motion using RANSAC [26]. After this, they are spatially clustered by performing a Delaunay triangulation on the set of feature points and subsequently isolated from the nonbackground points as follows: clusters of features are spatially grouped by disconnecting any edges connecting background points with nonbackground points, then performing a graph-based connected component analysis to identify isolated subgraphs. Alpha hulls [25] of these subgraphs form envelopes surrounding spatially isolated feature sets, which can be used to identify sets of image pixels.

B. Shape Extraction

The photometric properties of the foreground region are initially unknown and have to be extracted dynamically from the given image information. This information may change over time due to, e.g., changes in illumination. Therefore, an approach that can adapt to the dynamic statistical properties of the photometric information is necessary. Many techniques seek to model the background statistics of the image, such as background subtraction techniques. However, this information is often difficult to extract and is not usually relevant to a moving observer.
The object shape from an alpha hull can be extracted using gradient-based edge detection techniques, such as that in [20]. However, gradient information is typically susceptible to noise or even textured image regions.
Therefore, we propose two approaches of increasing computational intensity and accuracy that statistically estimate the foreground from the potential mixture of foreground and background enveloped by an alpha hull.The first approach, i.e., referred to here as single background-foreground boosting (SB-FB), estimates the foreground using a single foreground-background model, which assumes that the tracked object possesses different photometric properties from any part of the background immediately surrounding the object. This assumption is sufficient for a sparse-in-time shape estimation technique, where the object being tracked will be different sufficiently (photometrically) from the background.

c. Shape Memory for Object Tracking

Prior shape information is particularly useful in active-contour models to reduce the likelihood of the active contour deforming to unlikely configurations of shape. However, the prior shape information is difficult to obtain without manually segmenting and preparing suitable templates to be used for statistical modeling.

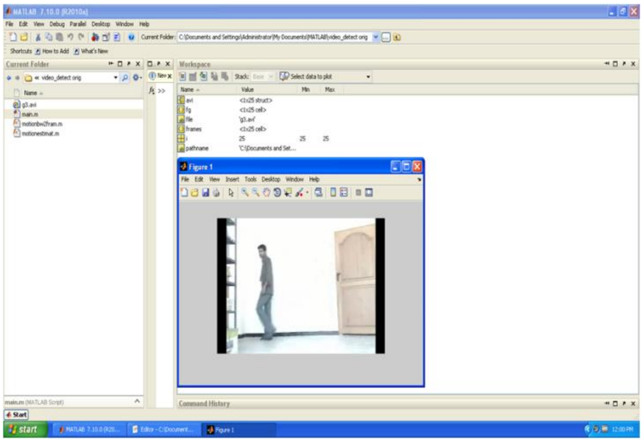

Fig 1.1
The input obtained from the database shown in fig 1.1

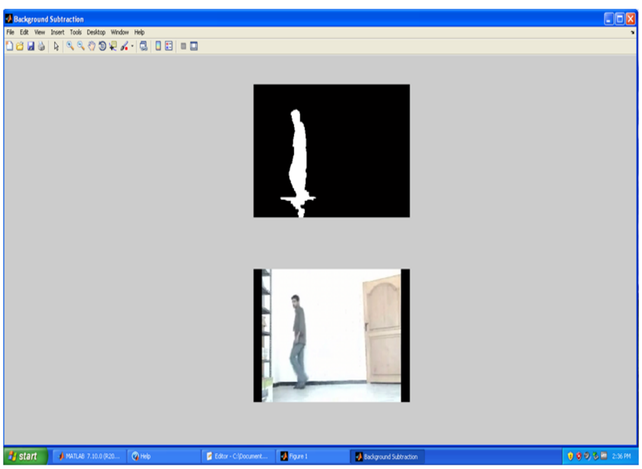

Fig 1.2
Background separated image from video fig1.2

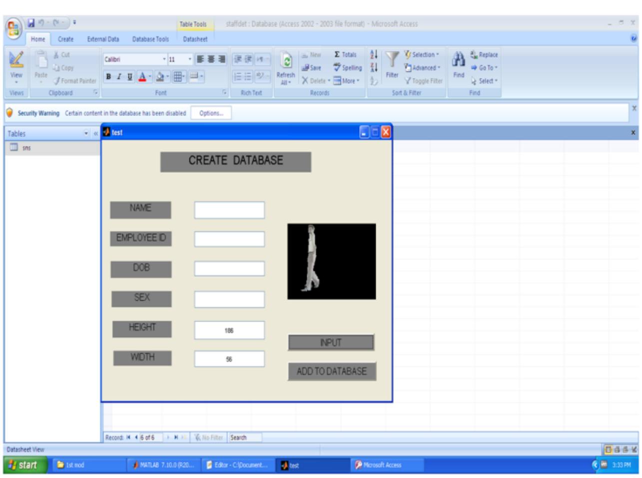

Fig 1.3
Gait implementable background separated video signal fig 1.3

IV. DISCUSSION AND CONCLUSION

A new fully automatic object segmentation and tracking framework has been proposed consisting of new techniques applicable not only to object tracking in video data but also to static image object segmentation. The results show that the system is capable of automatically detecting and tracking moving objects in video data without any manual intervention.Furthermore, comparison with other existing techniques configurations of techniques demonstrate similar or superior object tracking performance for the work described here. These developments proposed are not only theoretically interesting as the potential applications for such a system are quite wide, including security and multimedia. Further on the human gait parameters can be implemented in the tracked object and therefore the identification of the respective image stored in the database can be performed.

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