Active Vision Techniques for Visually Mediated Interaction

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Abstract

In this paper we introduce adaptive vision techniques used, for example, in video-conferencing applications. First, we present the recognition of identity, expression and head pose using Radial Basis Function (RBF) networks. Second, we address gesture-based communication and attentional focus, using colour/motion cues to direct face detection and capture 'attentional frames'. These focus the processing for Visually Mediated Interaction via an appearance-based approach with Gabor filter coefficients used as input to time-delay RBF networks. Third, we present methods for the gesture recognition and behaviour (user-camera) coordination in an integrated system.

Key ords: Visually Mediated Interaction; Face Recognition; Gesture Recognition; Camera Control; Time-Delay Neural Networks

1 Introduction

Visually Mediated Interaction (VMI) is a process of facilitating interaction between people, either remotely or locally, using visual cues for discourse/interaction management. In particular, gaze direction is often associated with diectic, attention-directing pointing to indicate objects or people of interest in the immediate context as part of the behavioural interaction.

We know that robust tracking of non-rigid objects such as human faces and bodies involved in machine analysis of this kind of interactive activity is difficult due to rapid motion, occlusion and ambiguities in segmentation and model selection. This was partially addressed by the move to active vision and dynamic models for robust tracking using sophisticated Kalman filters, as exemplified by Blake and others [1]. Recently, these have been specialised to allow the learning of complex hand dynamics [23]. More generally, research funded by British Telecom (BT) on *Smart Rooms* [38] and the ALIVE project [30] at MIT Media Lab has shown progress in the modelling and interpretation of human body activity. This used the *Pfinder* (Person Finder) system [49], which can provide real-time human body analysis. Further analysis to model the progression of ongoing activity involves techniques such as *Hidden Markov Models*

2 The RBF Network Scheme

The RBF network is a two-layer, hybrid learning network [32,33], which combines a supervised layer from the hidden to the output units with an unsupervised layer from the input to the hidden units. The network model is characterised by individual radial Gaussian functions for each hidden unit, which simulate the effect of overlapping and locally tuned receptive fields.

The RBF network is characterised by computational simplicity, supported by well-developed mathematical theory, and robust generalisation, powerful enough for real-time real-life tasks [42,43]. The nonlinear decision boundaries of the RBF network make it better in general for function approximation than the hyperplanes created by the multi-layer perceptron (MLP) with sigmoid units [41], and they provide a guaranteed, globally optimal solution via simple, linear optimisation. One advantage of the RBF network, compared to the MLP, is that it gives low f44Td(linear)Tj8-ed

Table 1
Body movement and behaviour definitions for the gesture database.

Gesture	Body Movement	Behaviour
pntrl	point right hand to left	pointing left
pntrr	point right hand to right	pointing right
wavea	wave right hand above head	urgent wave
waveb	wave right hand below head	non-urgent wave

Previous approaches to recognising human gestures from real-time video as a nonverbal modality for human-computer interaction have involved computing low-level features from motion to form *temporal trajectories* that can be tracked by Hidden Markov Models or Dynamic Time Warping. However, for this work we explored the potential of using simple image-based differences from video sequences in conjunction with the RBF network learning paradigm to account for variability in the appearance of a set of predefined gestures. The computational simplicity and robust generalisation of our alternative RBF approach provides giv0Td(p34ional)Tj76.f12.60T30.12Tf54.71990Td(geTd(the)Tj14.71990Td98(1jsui-

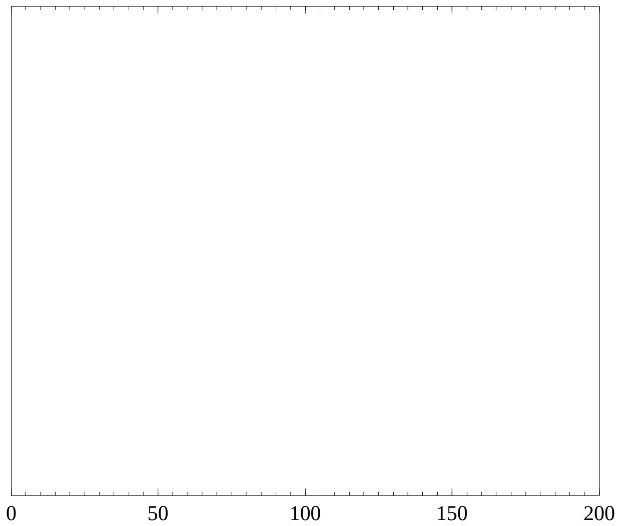

0
50
100
150
200

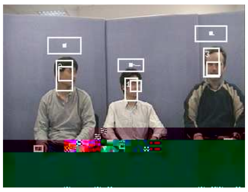
Table 2
Example interpretations of camera position vectors for group interaction scenarios with three people.

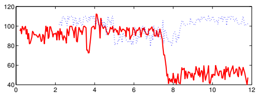
Camera Position Vector	Interpretation
`[0,0,0]`	frame whole scene
`[1,0,0]`	focus on subject A
`[0,1,1]`	focus on subjects B and C using a split-screen effect

While full computer understanding of dynamic visual scenes containing several people may be currently unattainable, we have investigated a computationally efficient approach to determine areas of interest in such scenes. Specifically, we have devised a method for modelling and interpretation of single- and multi-person human behaviour in real time to control video cameras [44]. Such machine understanding of human motion and behaviour is currently a key research area in computer vision, and has many real-world applications. *Visually Mediated Interaction* (VMI) is particularly important to applications in video telecommunications. VMI requires intelligent interpretation of a dynamic visual scene to determine areas of interest for effective communication to remote users.

As we have seen, our general approach to modelling behaviour is *appearance-based* in order to provide real-time behaviour interpretation and prediction [20,44]. In addition, we only use defined as any body movement sequence that is performed subconsciously by the participant, and here, it is head pose that is the primary source of implicit behaviour.

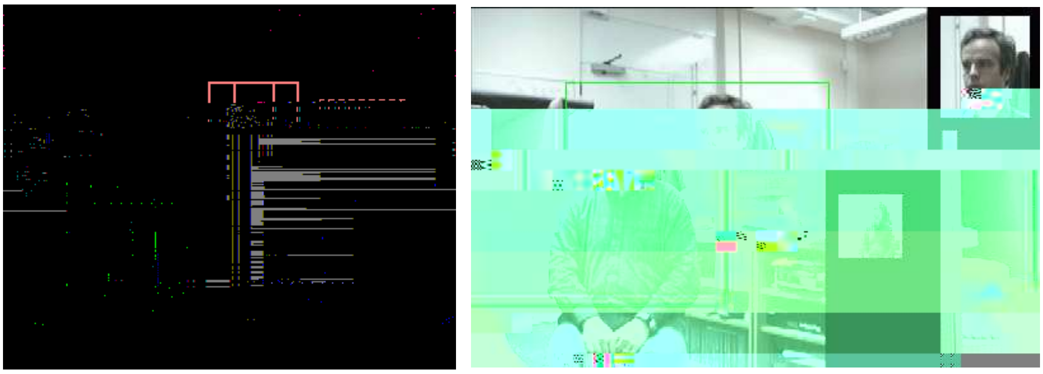
However, head pose information may be insufficient to determine




120
100
80
60
40
0
2
4
6
8
10
12

- Pre-defined gestures and head pose of several individuals in the scene can be simultaneously recognised for interpretation of the scene.
- A scene vector-to-camera control transformation can be performed via a TDRBF network, using example-based learning.

We have been able to show how multi-person activity scenarios can be learned from training examples and interpolated to obtain the same interpretation for



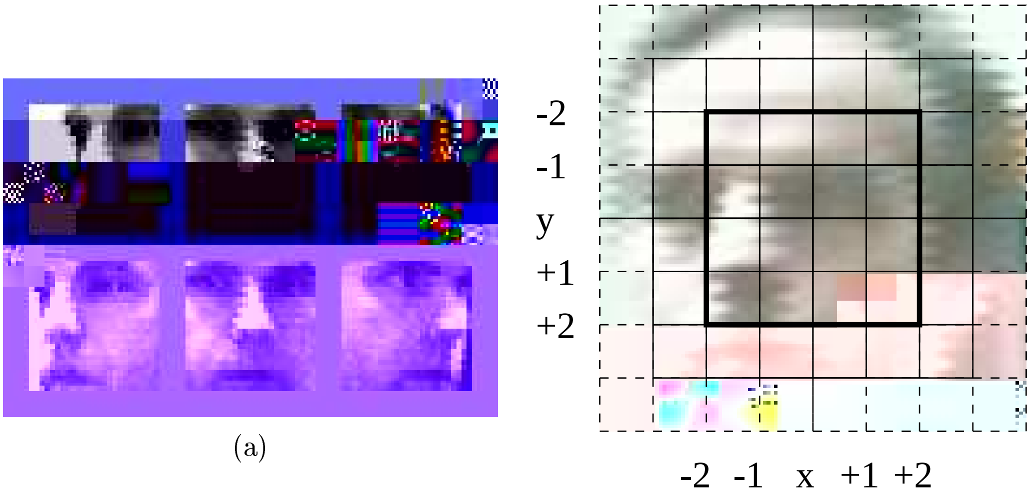
(a) (b)

Fig. 5. Use of colour/motion information to position an attentional frame around a person: (a) a box is centred around each colour/motion 'blob', the inner vertical lines representing the standard deviation of the pixels along the x-axis, giving a width measure, (b) having identified which box contains the head (the uppermost one in (a)), an attentional frame box is drawn around the person relative to the head position, and sized according to head width. The top right image shows the image area inside the head box, bottom right the resampled area of the image inside the attentional frame.

to give a binary map of moving skin pixels within the image, and we used local histogram maxima to identify potential 'blob' regions. A box which was large enough to contain the head at all distances in our target range was then fitted over the centroid of each of these regions. Fig. 5(a) shows how each box is centred on the centroid of each maximum, with the inner lines showing the standard deviation of the pixels along the x-axis from that centroid. It can also be seen that the hands are ignored in this example, as they are too low down to be included in a face-size 'blob'.

A robust approach to head tracking using colour/motion blobs is what we call *temporal matching*: the tracker only considers blobs from the current frame which have been matc28bc57centroid.usingbtface-size

fa57-a0Td[(b)-mtbnjEthinhead



(a) (b)

Fig. 6. (a) Two methods for segmenting 25×25 pose-varying face data: (top row) nose-centred, (bottom row) face-centred, the former being used for experiments here, (b) the grid system for detecting potential faces within a potential 'head blob' region of the image: each area tested is represented by a 4×4 box, the thick line shows the central position $(x, y = 0)$, normal line and dashed lines

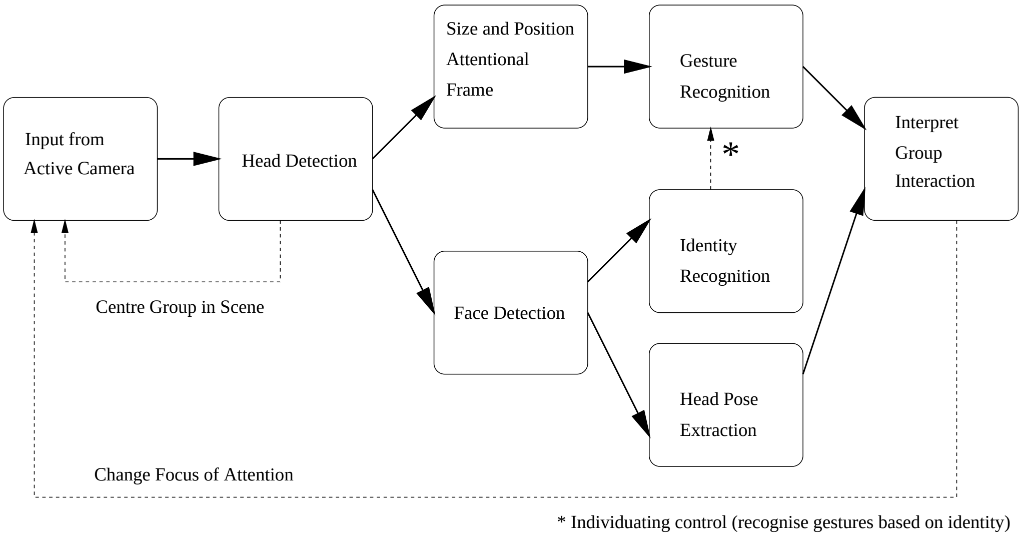


Fig. 7. A block diagram outlining the integrated system (from [22]).

qualitative level of head-pose was found to be very useful for group interaction analysis

of high-level models such as *Bayesian Belief Networks* (BBNs) might provide a combination of hand-coded *a priori* information with machine learning to ease training set requirements. This is because the BBNs model the decomposition of the problem and it is the model parameters (conditional probabilities) that are learnt so that higher level inferences can be made from low level visual evidence (see, for example, [7]).

6 Conclusions and Further Research

It is clear that there are many potential advantages of Visually Mediated Interaction with computers over traditional keyboard/mouse interfaces. For example, removing system-dependant IT training and allowing the user a more intuitive form of system direction. However, we have also seen that there are still many challenges for integrating multi-user interaction analysis and control due to the ambiguities and combinatorial explosion of possible behavioural interactions. We have demonstrated how our connectionist techniques can support real-time interaction by detecting faces and capturing 'attentional frames' to focus processing. To go further we will have to build our VMI systems around the task demands which include both the limitations of our techniques and potentially conflicting intentions from users. Connectionist techniques are generally well suited to this kind of situation as they can learn adaptive mappings and have inherent constraint satisfaction.

Further research is taking two main directions: 1) the development of gesture-based control of animated software agents in the EU Puppet project; and 2) the development of context-based control in more complex scenarios in the new EU Actipret project. The first (e.g. the GestureBall application) extends the use of symbolic (action selection) and mimetic (dynamic control) functions in gesture-based interfaces where pointing can indicate the current avatar and movement patterns can control animation parameters. The second involves recognition of complex behaviours and activities that consist of a sequence of events that evolve over time [16,17]. As yet there has been little work that combines automated learning of behaviours in different contexts. In other words, it is usually only simple, generic models of behaviour that have been learnt rather than learning when and how to apply more complex models in a context sensitive manner.

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