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Efficient Structure Learning of Bayesian networks Using Constraints

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ABSTRACT:- *Automated analysis of human affective behavior has attracted increasing attention from researchers in psychology, computer science, linguistics, neuroscience, and related disciplines. Promising approaches have been reported, including automatic methods for facial and vocal affect recognition. Facial activities are characterized by three levels. First, in the bottom level, facial feature points around each facial component, i.e., eyebrow, mouth, capture the detailed face shape information. Second, in the middle level, facial action units, represent the contraction of a specific set of facial muscles, i.e., lid tightener,eyebrow raiser, etc.Finally,in the top level, six prototypical facial expressions represent facial muscle movement. A unified probabilistic framework based on the dynamic Bayesian network to simultaneously and coherently represent the facial evolvement in different levels, their interactions and their observations. Advanced machine learning methods are introduced to learn the model based on both training data and subjective prior knowledge.*

Keywords:- *Bayesiannetwork,expression recognition, facial action unit recognition, facial feature tracking, simultaneous tracking and recognition*

I. INTRODUCTION

The recovery of facial activities in image sequence is an important and challenging problem. The facial activity model is constructed online. During the online recognition various computer vision techniques are used to track the facial feature points, and to get the Measurements are then used as evidence to infer the true states of the three level facial activities simultaneously.For example, facial feature tracking can be used in the feature extraction stage in expression/AUs recognition, and expression/AUs recognition results can provide a prior distribution for facial feature points. However, most current methods only track or recognize the facial activities in one or two levels, and track them separately, either ignoring their interactions or limiting the interaction to one way.

In addition, the estimates obtained by image-based methods in each level are always uncertain and ambiguous because of noise, occlusion and the imperfect nature of the vision algorithm. Probabilistic model based on the Dynamic Bayesian Network (DBN) to capture the facial interactions at different levels. Hence, in the model, the flow of information is two-way, not only bottom-up, but also top-down. In particular, not only the facial feature tracking can contribute to the expression/AUs recognition, but also the expression/AU recognition helps to further improve the facial feature tracking performance. Given the proposed model, all three levels of facial activities are recovered simultaneously through a probabilistic inference by systematically combining the measurements from multiple sources at different levels of abstraction. The proposed facial activity recognition system consists of two main stages: offline facial activity model construction and online facial motion measurement and inference. Using training data and subjective domain observations, all three levels of facial activities are estimated simultaneously through a The graphical representation of the traditional tracking algorithm, i.e., Kalman Filter, is shown in figure measurements of facial motions, i.e., AUs.This probabilistic interference by systematically integrating visual.

II. RELATED WORKS

2.1 Facial feature tracking

Facial feature points encode critical information about face shape and face shape deformation. Accurate location and tracking of facial feature points are important in the applications such as animation, computer graphics, etc. Generally, the facial feature points tracking technologies could be classified into two categories: model free and model-based tracking algorithms.

2.2 Expression/AUs Recognition

Facial expression recognition systems usually try to recognize either six expressions or the AUs. Over the past decades, there has been extensive research on facial expression analysis [9], [14], [16].Current methods in this area can be grouped into two categories: image-based methods and model-based methods. Image-based approaches, which focus on recognizing facial actions by observing the representative facial appearance changes, usually try to classify expression or AUs independently and statically. This kind of method usually consists of two key stages. First, various facial features, such as optical flow [9], [10], explicit feature measurement, Haar features, Local Binary Patterns (LBP) features, independent component analysis (ICA) feature points, Gabor wavelets , etc., are extracted to represent the facial gestures or facial movements. Given the extracted facial features, the expression/AUs are identified by recognition engines, such as Neural Networks, Support Vector Machines (SVM), rule-based approach, AdaBoost classifiers, Sparse Representation (SR) classifiers, etc.

2.3 Simultaneous Facial Activity Tracking/Recognition

Firstly a DBN model is built to explicitly model the two-way interactions between different levels of facial activities. In this way, not only the expression and AUs recognition can benefit from the facial feature tracking results, but also the expression recognition can help improve the facial feature tracking performance. Secondly, recognize all three levels of facial activities simultaneously. Given the facial action model and image node is introduced to control the dynamic system.

III. FACIAL ACTIVITY MODELING

3.1 Overview of the Facial Activity Model

3.1.1 Single Dynamic Model:

In Fig.1 *Xt* is the current hidden state, e.g., image coordinates of the facial feature points, we want to track and *Mt* is the current image measurement (Hereafter, the shaded nodes represent measurements, i.e., estimates, and the unshaded nodes denote the hidden states). The directed links are quantified by the conditional probabilities, e.g., the link from *Xt* to *Mt* is captured by the likelihood *P(Mt |Xt)*, and the link from *Xt*−1 to *Xt* by the first order dynamic *P(Xt |Xt*−1).

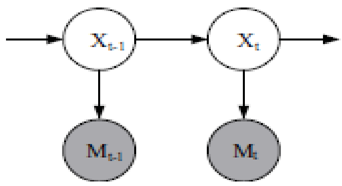

Fig.1Traditional tracking model

3.1.2 Dynamic model with switching node

The above tracking model has only one single dynamic *P(Xt |Xt−1)*, and this dynamic is fixed for the whole sequence. But for many applications, the dynamic can “switch” according to different states. Therefore, researchers introduce a switch node to control the underling dynamic system [28], [29]. For the switching dynamic model, the switch node represents different states and for each state, there are particular predominant movement patterns. The works in [26] and [30] also involved multi-dynamics, and their idea can be interpreted asthe graphical model in Fig. 2.

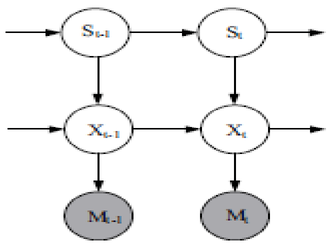

Fig.2 tracking model with switch node

3.1.2 Our facial activity model:

Dynamic Bayesian network is a directed graphical model, and compared to the dynamic models above, DBN is more general to capture complex relationships among variables. We propose to employ DBN to model the spatiotemporal dependencies among all three levels of facial activities (facial feature points, AUs and expression)as shown in Fig.3. The *Et* node in the top level represents the current expression; *AUt* represents a set of AUs; *Xt* denotes the facial feature points we are going to track; *MAUt* and *MXt* are the corresponding measurements of AUs and the facial feature points, respectively. The three levels are organized hierarchically in a causal manner such that the level above is the cause while the level below is the effect. Specifically, the global facial expression is the main cause to produce certain AU configurations, which in turn cause local muscle movements, and hence feature points movements. For example, a global facial expression (e.g., Happiness) dictates the AU configurations, which in turn dictates the facial muscle movement and hence the facial feature point positions.

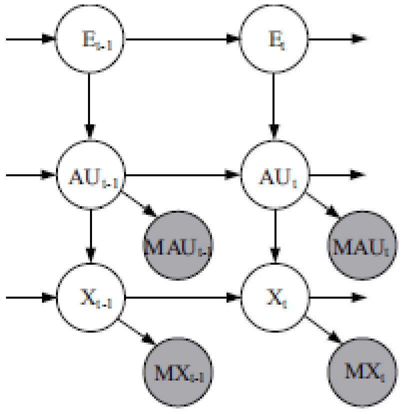

Fig.3Proposed activity model

3.2 Modeling the relationships between facial features and AUs

Modeling the relationships between facial feature points and AUs (*CB/E/N/M* are the intermediate nodes;*X*Eyebrow/Eye/Nose/Mouth are the facial feature nodes around each face component and *M*Eyebrow/Eye/Nose/Mouth are the corresponding measurement nodes). the spatiotemporal dependencies among all three levels of facial activities (facial feature points, AUs and expression) as shown in Fig.4

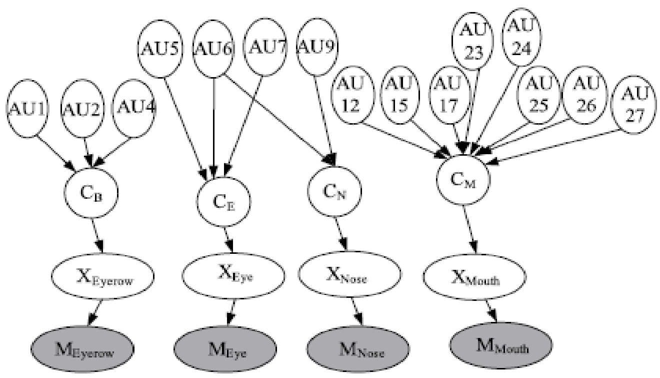

Fig.4Relationship between facial point and AU

3.3 Modeling semantic relationships among AUs

We modeled the relationships between facial feature points and AUs. Detecting each AU statically and individually is difficult due to the variety, ambiguity, and dynamic nature of facial actions, as well as the image uncertainty and individual differences. Moreover, when AUs occur in a combination, they may be no additive: that is, the appearance of an AU in a combination is different from its standalone appearance. Fortunately, there are some inherent relationships among AUs, as described in the FACS manual [1]. We can summarize the relationships among AUs into two categories, i.e., co-occurrence relationships and mutual exclusion relationships. The co-occurrence relationships characterize some groups of AUs, which usually appear together to show meaningful facial displays, e.g., AU1+AU2+AU5+AU26+AU27 to show surprise expression; AU6+AU12+AU25 to show happiness expression; AU1+AU4+AU15+AU17 to show sadness expression.

On the other hand, based on the alternative rules provide in the FACS manual, some AUs are mutually exclusive since "it may not be possible anatomically to do both AUs simultaneously" or "the logic of FACS precludes the scoring of both AUs" [1]. For instance, one cannot perform AU25 (lip part) with AU23 (lip tightener) or AU24 (lip presser) simultaneously. The rules provided in [1] are basic, generic and deterministic. They are not sufficient enough to characterize all the dependencies among AUs, in particular some relationships that are expression and database dependent. Hence, in this paper, we propose to learn from the data to capture additional relationships among AUs.

3.4 Modeling the relationships between AUs and expression

In this section, we will add Expression node at the top level of the model. Expression represents the global face movement and it is generally believed that the six basic expressions (happiness, sadness, anger, disgust, fear and surprise) can be described linguistically using culture and ethnically independent AUs, e.g., activating AU6+AU12+AU25 produces happiness expression, as shown in Fig. 5(a).

We group AUs according to different expressions as listed in Table II. But inferring expression from AUs is not simply to transfer the combination of several AUs directly to certain expression. Naturally, combining AUs belonging to the same category increases the degree of belief in classifying to that category, as shown in Fig. 6(a) (the combination of AU6 and AU12 increases the likelihood of classifying as happiness). However, combining AUs across different categories may result in the following situations: First, an AU combination belonging to a different facial expression, e.g., when AU1 occurs alone, it indicates a sadness, and when AU5 occurs alone, it indicates a surprise, however, the combination of AU1 and AU5 increases the probability of fear as shown in Fig.5(b); Second, increasing ambiguity, e.g., when AU26 (jaw drop), an AU for surprise, combines with AU1, an AU for sadness, the degree of belief in surprise is reduced and the ambiguity of classification may be increased as illustrated in Fig.5(c)

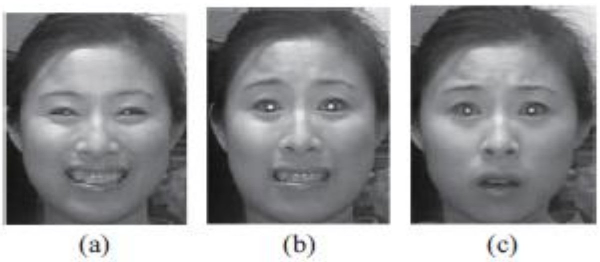

Fig.5AU combinations (a)AU12+AU6 gives happiness (b)AU1+AU5 becomes fear (c)AU26+AU1 increases ambuigty between fear and surprise

Table I: List OF Action Unit

AU1	**Inner brow raiser**
AU2	Outer brow raiser
AU4	Brow lowerer
AU5	Upper lid raiser
AU6	Cheek raiser
AU7	Lid tightener
AU9	Nose wrinkle
AU12	Lip corner puller
AU15	Lip corner depressor

IV. CONCLUSION

A hierarchical framework based on Dynamic Bayesian network for simultaneous facial feature tracking and facial expression recognition By systematically representing and modeling inter relationships among different levels of facial activities, as well as the temporal evolution information, the proposed model achieved significant improvement for both facial feature tracking and AU recognition, compared to state of the art methods.The improvements for facial feature points and AUs come mainly from combining the facial action model with the image measurements. Specifically, the erroneous facial feature measurements and the AU measurements can be compensated by the model's build-in relationships among different levels of facial activities, and the build-in temporal relationships. Since model systematically captures and combines the prior knowledge with the image measurements, with improved image-based computer vision technology, system may achieve better results with little changes to the model.

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