

Vision and Attention Theory Based Sampling for Continuous Facial Emotion Recognition

Albert C. Cruz, *Student Member, IEEE*, Bir Bhanu, *Fellow, IEEE*, and
Ninad S. Thakoor, *Member, IEEE*

Abstract—Affective computing—the emergent field in which computers detect emotions and project appropriate expressions of their own—has reached a bottleneck where algorithms are not able to infer a person’s emotions from natural and spontaneous facial expressions captured in video. While the field of emotion recognition has seen many advances in the past decade, a facial emotion recognition approach has not yet been revealed which performs well in unconstrained settings. In this paper, we propose a principled method which addresses the temporal dynamics of facial emotions and expressions in video with a sampling approach inspired from human perceptual psychology. We test the efficacy of the method on the Audio/Visual Emotion Challenge 2011 and 2012, Cohn-Kanade and the MMI Facial Expression Database. The method shows an average improvement of 9.8% over the baseline for weighted accuracy on the Audio/Visual Emotion Challenge 2011 video-based frame-level subchallenge testing set.

Index Terms—Facial expressions, Audio/Visual Emotion Challenge, Sampling and Interpolation

1 INTRODUCTION

FACIAL emotion recognition has applications in human-computer interaction, medical, advertising, and action recognition for computer games.

An emergent application of *Affective Computing* incorporates facial emotion and expression recognition. An embodied agent senses a person’s emotion and projects an appropriate expression in response [1]. This facilitates non-verbal communication between a person and a computer, thus, improving feedback between them. However, state-of-the-art algorithms do not generalize to unconstrained data, presenting a challenge to this field.

Current methods perform well on datasets acquired in controlled situations, e.g. the Japanese Female Facial Expression database [2], Cohn-Kanade (CK) [3], the MMI Facial Expression Database (MMI-DB) [4], and the Facial Emotion Recognition and Analysis (FERA) challenge dataset [5]. However, the

Audio/Visual Emotion Challenge (AVEC) datasets [6], [7] present difficult challenges. With previous datasets, each dataset was small enough to be loaded into memory at once, even for cases of high feature dimensionality. Previous approaches could reduce the number of frames to be processed by taking advantage of apexes of emotions, such as in CK. The most intense and discriminative frames corresponding to the apexes were labeled so a method could choose to retain them only.

The AVEC datasets explore the problems of a continuous emotion dataset, where it is computationally undesirable to select all the frames for processing. There are approximately one and a half million frames of video. The expressions in the dataset are subtle, spontaneous, and difficult to detect. The people in the videos are expressing emotions in a natural setting. The videos are not segmented. The apex labels are not given and it may be difficult to detect them automatically. In this paper, we propose a principled method for downsampling the frames for facial emotion and expression recognition. The method is inspired by the behavior of the human visual system. It can take advantage apexes if they are provided, but they are not required.

The rest of the paper is organized as follows: Section 2 discusses related work, motivations and contributions. Section 3 details the proposed downsampling method, and the full emotion recognition pipeline. Section 4 provides dataset information, parameters and results on AVEC 2011, AVEC 2012, CK and MMI-DB. Section 5 presents the conclusions of the paper.

2 MOTIVATION, RELATED WORK AND CONTRIBUTIONS

The motivation for sampling and reducing memory cost in large datasets is given in Section 2.1. A survey of related work, entries to the AVEC datasets, and other downsampling methods is given in Section 2.2. The contributions of this paper are given in Section 2.3.

• A. C. Cruz, B. Bhanu and N. S. Thakoor are with the Center for Research in Intelligent Systems, University of California, Riverside, Winston Chung Hall 216, Riverside, CA, 92521-0425, USA.
E-mail: {acruz,bhanu,ninadst}@ee.ucr.edu.
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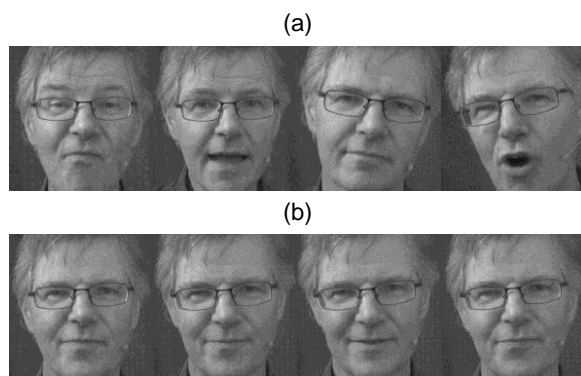


Fig. 1: Two different segments of AVEC [6] development video 14. (a) Many frames are required to describe the person's pose change and facial expressions. (b) The person is less expressive, and the segment needs few frames to be described.

2.1 Motivation

In the AVEC datasets, videos are captured at a high frame rate and over a long period of time. This makes it difficult to train a model for classification using all the frames in the dataset. An easy solution is to temporally downsample the video at a uniform, low frame rate. Unfortunately, this procedure results in a loss of precision, as it does not have the ability to precisely detect when the emotion changes. A dynamic sampling rate is desired that assigns a lower frame rate to parts of the video where the person is idle, and a higher frame rate to parts of the video where the person is animated. For example, in Figure 1, there are two different segments of the same video which merit different sampling rates. In Figure 1(a), the person is changing his pose, opening his mouth, furrowing his brow, using his cheek muscles, and raising his eyebrows. Many frames are needed to describe this segment. In Figure 1(b), the person holds his expression, so this segment would need only a few frames to be described. Therefore, we propose a method that applies a *dynamic sampling rate* which would allocate less frames for data analysis when the individual is idle, and more when the individual is active. The large volume of data poses the following problems to a downsampling procedure:

(1) With the AVEC datasets, processing each frame would be too costly. The downsampling should occur as early as possible in the video processing pipeline. Though related work [8], [9] propose dynamic downsampling, these methods prune samples *late* in the recognition pipeline, in classification.

(2) Use of the apex label is popular in facial expression and emotion recognition, and results show that features from the apex region improve classification rates [10]–[12]. However, the apexes must be *manually* labeled by an expert. If an algorithm is used to detect the apexes, the labeling can have errors. Situations may arise in the AVEC datasets where expressions are so subtle that extracting apex information is a difficult

task for both humans and computers. There is a need for annotation free facial emotion and expression recognition. Our method does not require apex labels.

2.2 Related Work

In the baseline visual system for FERA [5] and the AVEC datasets [6], [7], face region-of-interest (ROI) is extracted which is then aligned by eye corner points. Subsequently, Local Binary Patterns (LBP) [26] are extracted as histogram-based features, and the emotions are classified with a support vector machine (SVM). In [24], the top approach for discrete emotions on the FERA dataset, Yang and Bhanu introduced a novel registration procedure called avatar image registration. It was found that a better registration method greatly improved performance. In [23], Valstar et al. tracked 20 fiducial facial points and classified them using a probabilistic actively learned SVM.

AVEC 2011 challenge [6]: In [20], Ramirez et al. quantified eye gaze, smile and head tilt with a commercial software (Omron OKAO Vision and Fraunhofer Sophisticated High-speed Object Recognition Engine) and used a Latent-Dynamic Conditional Random Field (LDCRF) [27] classifier. In [13], Glodek et al. modelled their system after the human perception's capability to separate form and motion. Gabor filters captured spatial information, and correlation features captured temporal information. The features were fed into multiple stages of filtering and non-linear pooling to further simulate human perception. In [8], Dahmane and Meunier proposed an approach for representation of the response to a bank of Gabor energy filters with histograms. A SVM with a radial basis function was used as a classifier.

AVEC 2012 challenge [7]: In [18], Nicolle et al. used 3-D model fitting, and global and local patch-based appearance features. These features were extended temporally with log-magnitude Fourier spectrum. A correlation based feature selector was proposed and a Nadaraya-Watson estimator was used as a classifier. During ground-truth labelling, the expert watches the video, and then notes changes in the label. There is a time delay between the actions in the video, and when the expert notes the change. Their method accounted for this delay. In [22], Soladi et al. employed two active appearance models, one to quantify head pose, and one to quantify smile. A *Mamdani* type fuzzy inference system was used. The features included who the person was speaking with, duration of sentences, and how well engaged the person was in the conversation with the embodied agent. In [16], Maaten used the baseline features, the derivative of features, and L_2 -regularized linear least-squares regression. In [19], Ozkan et al. proposed a concatenated hidden Markov model (co-HMM). The label intensity values were discretized into bins. A HMM was trained to detect a specific bin, e.g., if there were ten quantization levels,

TABLE 1: Review of Related Work. AAM: active appearance model. AIR: avatar image registration. CRF: conditional random field. HMM: hidden Markov model. LBP: local binary patterns. LLS: linear least squares. LPQ: local phase quantization. MHI: motion history images. SVM: support vector machine.

Approach	Downsampling	Registration	Features	Classifier	Dataset
AVEC 2012 Baseline [7]	Fusion of 50 frames	Eye-point	LBP	SVM	AVEC 2012 [7]
Dahmane and Meunier [8]	Change granularity if label changes	Eye-point ¹	Histograms of Gabor	SVM	AVEC 2011 [6]
Glodek et al. [13]	Random	Eye-point ¹	Gabor, temporal correlation	SVM, HMM	AVEC 2011 [6]
Jiang et al. [14]	Random, bootstrapping, heuristic	Eye-point	LPQ from Three Orthogonal Planes	SVM, modelling of temporal phases	FERA [5], MMI-DB [4], SAL, UNBC-McMaster pain
Koelstra et al. [15]	X	Affine	MHI, orientation histograms	Gentleboost, HMM	MMI-DB [4], CK [3]
Maaten [16]	X	Eye-point ¹	LBP	LLS	AVEC 2012 [7]
Meng and Bianchi-Berthouze [17]	X	Eye-point ¹	LBP	Multi-HMM	AVEC 2011 [6]
Nicolle et al. [18]	X	Point distribution model	Eigenappearance, log-magnitude Fourier spectra	Nadaraya-Watson	AVEC 2012 [7]
Ozkan et al. [19]	X	Commercial	Commercial, frame number	Level quantization, co-HMM	AVEC 2012 [7]
Ramirez et al. [20]	X	Commercial	Commercial	Latent-dynamic CRF	AVEC 2011 [6]
Savran et al. [21]	Select outlier frames based on standard deviation	Eye-point ¹	Local appearance statistics	Bayesian filtering fusion	AVEC 2012 [6]
Soladi et al. [22]	X	AAM	Statistics of head pose	Fuzzy inference system	AVEC 2012 [6]
Valstar et al. [23]	X	Particle filtering with factorized likelihoods	Fiducial facial points	Probabilistic active learning SVM	MMI-DB [4], CK [3]
Wu et al. [10]	X	None stated	Spatiotemporal Gabor	Bootstrapping, SVM	CK [3]
Yang and Bhanu [24]	X	AIR	LBP and LPQ	SVM	FERA [5]
Zhu et al. [9]	Bootstrapping to select frames based on apexes	AAM, eye-point	Tracker points, SIFT	AdaBoost	RU-FACS [25]
Proposed Method	Dynamic sampling based on changes in visual information with or without apex	AIR	LBP	SVM	AVEC 2011/2012 [6], [7], MMI-DB [4], CK [3]

1 then there would be ten classifiers each detecting if
2 that specific level was present. A final HMM fused
3 these outputs at the decision level. In the video-
4 based approach in [21], Savran et al. extended local
5 appearance features to the temporal domain by taking
6 the mean and standard deviation in sliding temporal
7 windows. AdaBoost was used a feature selector, and
8 ϵ -support vector regression (SVR) was used to regress
9 the labels.

10 *Sampling methods:* Some approaches have attempted
11 to address the sampling issue. In [13], Glodek ran-
12 domly sampled the video frames. In [8], a downsam-
13 pling method was proposed that changed granular-
14 ity of sampling based on whether or not a change
15 was detected in the predicted label. A limitation of
16 this system is that it assumes that the system can
17 correctly predict the label. In [9], Zhu et al. reduced
18 the number of frames in the dataset with a boot-
19 strapping procedure. This method requires the apexes
20 to be labeled. We propose a method that does not
21 require peak frame labeling. In [21], Savran et al.
22 downsampled the training data to frames that had an
23 emotion label intensity greater than $\pm\sigma$ from the mean
24 emotion intensity. No framework for downsampling
25 test data was provided. In [14], Jiang et al. pro-
26 posed a texture descriptor that extended Local Phase
27 Quantization (LPQ) features to the temporal domain.

It was called Local Phase Quantization from Three
Orthogonal Planes. The paper also investigated three
downsampling methods: randomly selecting frames,
bootstrapping, and a heuristic approach that found
two subsets of the data to describe static appearance
descriptors and dynamic appearance descriptors. It
was found that the heuristic method was the best
performer. All of these methods have focused on
training data selection, and no method was given to
downsample the testing data. A summary of related
work is given in Table 1. As compared to the previous
related work, the contributions of this paper are given
below.

2.3 Contributions

We propose emulating the behavior of the human
visual system to address the challenges in the AVEC
datasets. The focus of work in this paper is video-
based temporal sampling. The contributions of this
paper are: (1) We exploit vision and attention theory
[28], [29] from perceptual psychology to determine
an appropriate sampling rate. We assign a dynamic,
temporal granularity that is inversely proportional to
how frequent the visual information on a person's face
is changing. The method improves average correlation
with the ground-truth for all affect dimensions on
the AVEC 2012 frame-level subchallenge testing set

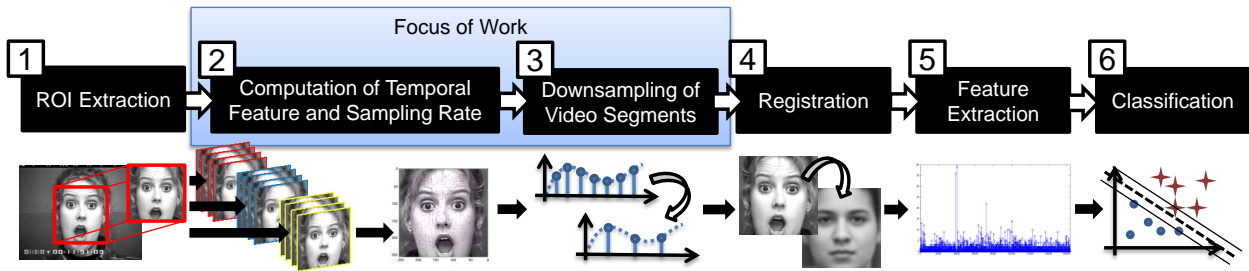


Fig. 2: System overview. (1) Extraction of ROI. (2) Partitioning of video into smaller segments, formation of temporal feature that quantifies motion, and computation of the dominant frequency of the temporal feature. (3) Downsampling of the video segment. (4) Registration of frames. (5) Appearance feature extraction. (6) Classification/regression.

1 over the baseline approach by a factor of 2.7. (2)
 2 We provide a framework for the method to integrate
 3 information from apex labels, if they are provided.
 4 The method improves average F_1 measure across 14
 5 different classes by 7.6 over [24]. (3) We provide a
 6 framework for using match-score fusion temporally.
 7 The method improves average weighted accuracy on
 8 all classes on the AVEC 2011 frame-level subchallenge
 9 development set over the use of uniform sampling of
 10 1 frame per segment and no fusion by 5.4%.

3 TECHNICAL APPROACH

12 When viewing a natural scene, the human visual sys-
 13 tem exhibits a saccade-fixation-saccade pattern [30].
 14 *Fixations* are moments of attention, where visual
 15 information is being processed. *Saccades* are rapid
 16 movements of eyes, where information is not being
 17 processed. First the eyes saccade, then fixate, and
 18 this procedure is repeated. The latency between two
 19 saccades decreases with the increasing frequency of
 20 temporal changes of visual information in the scene.
 21 We propose a method that emulates this process for
 22 emotion and expression recognition. Human percep-
 23 tion of faces is different than recognition of scenes
 24 or other objects. However, the focus of work is the
 25 concept of *attention*, the length of focus on a scene,
 26 not recognition. The temporal frequency of visual in-
 27 formation in the scene affects the amount of attention
 28 given to a part of the scene. Our algorithm is inspired
 29 by this physical process and emulates attention by
 30 downsampling a video.

31 The overview of this work is shown in Figure 2:
 32 (1) face ROI is detected with Viola-Jones [31]. (2)
 33 The video is partitioned into segments. Within each
 34 segment, the visual information is quantified with
 35 temporal features. We apply a discrete Fourier trans-
 36 form to the temporal feature to find the *dominant*
 37 *frequency*, the frequency of the temporal feature with
 38 the most energy. (3) The video is downsampled at
 39 the dominant frequency. (4) The selected frames after
 40 the downsampling are aligned with avatar image reg-
 41 istration [24]. (5) Appearance features are gener-
 42 ated in local regions. (6) Initial *a posteriori* prob-
 43 abilities of emotion labels in each frame in the video segment are

1 generated from SVM [32]. The results are temporally
 2 fused at the match-score level [33] to generate the
 3 final predicted labels. Section 3.1 discusses down-
 4 sampling for continuous videos, Section 3.2 discusses
 5 downsampling when apex labels are given. The full
 6 emotion recognition pipeline is described in Section
 7 3.3.

3.1 Downsampling Continuous Video

9 Downsampling of a continuous video without time
 10 annotations for apexes is done as data comes in. The
 11 videos are segmented into uniformly sized smaller
 12 segments. Each segment is downsampled *dynamically*,
 13 and each segment has its own appropriate down-
 14 sampling factor. Conventionally, each segment would
 15 be processed with a *uniform* downsampling factor.
 16 Pseudocode for the downsampling method is given in
 17 Algorithm 1.

3.1.1 Time partitioning procedure

18 The video I is segmented into equally sized non-
 19 overlapping segments of N frames. The segment of
 20 video I_Φ contains the frames at indices Φ where
 21 $\Phi = \{m_0, m_0 + 1, \dots, m_0 + N - 1\}$. The downsampled
 22 video segment I_{Φ^*} contains the frames at indices Φ^* ,
 23 where Φ^* is a subsequence of Φ . Initially, the system
 24 delays for N frames, and processes a video segment
 25 of N frames at a time. We start with $m_0 = 0$, so the
 26 first N frames form one segment. Then $m_0 = N$, so the
 27 frames from N to $2N - 1$ form another segment and so
 28 on, until the end of the video. If there is a remainder,
 29 it forms its own segment. We chose parameter N such
 30 that the duration of each segment is 1 s because 1 Hz
 31 is the maximum bound of the HVS according to vision
 32 and attention theory [30].

3.1.2 Computing the temporal feature

34 I_{Φ^*} is created by resampling I_Φ at a lower frequency.
 35 The first step is to quantify facial expressions into a
 36 signal that varies with time. The signal's frequency
 37 must respond to changes of facial expression. Because
 38 the frame rate is high, and the ROI is a frontal face,
 39 optical flow can be exploited to quantify the facial
 40 expressions [34]. ΔI_n is optical flow between the
 41

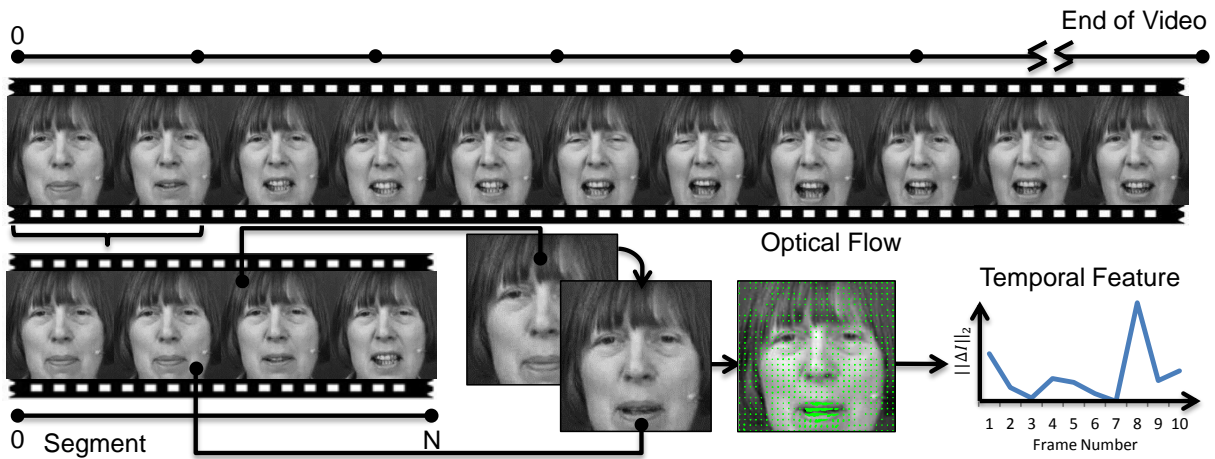


Fig. 3: Overview of how the temporal feature is computed. The video is segmented into non-overlapping segments of length N . Optical flow is computed using a pair of adjacent frames. The result of the optical flow forms the temporal feature.

1 frames I_n and I_{n-1} . It outputs a motion vector. The
 2 magnitude is summed for all pixels in an image to
 3 form a 1-D signal:

$$f(n) = \sum_{\mathbf{x}} \|\Delta I_n(\mathbf{x})\|_2 \quad (1)$$

4 where $f(n)$ is the temporal feature for a single frame,
 5 \mathbf{x} is a pixel, and $\|\cdot\|_2$ is the magnitude. For the entire
 6 segment I_Φ , the temporal feature \mathbf{f}_Φ is indicated by:
 7 $\mathbf{f}_\Phi \equiv [f(m_0), f(m_0 + 1), \dots, f(m_0 + N - 1)]$. Figure 3
 8 shows how the video is segmented, how the optical
 9 flow is computed, and how the temporal feature is
 10 generated. As registration is costly, to reduce the
 11 number of frames to be registered, we compute the
 12 optical flow before registration. We do not use optical
 13 flow as a feature for classification, or for alignment.

14 3.1.3 Downsampling the video segment

15 To compute the dominant frequency, first, the DC-
 16 offset is removed:

$$\tilde{\mathbf{f}}_\Phi = \mathbf{f}_\Phi - E(\mathbf{f}_\Phi) \quad (2)$$

17 where $E(\cdot)$ is the mean. It is important to remove
 18 the DC-offset for two reasons: (1) it normalizes the
 19 temporal feature and (2) for real data, the $\mathbf{F}_\Phi(0)$ -
 20 corresponding to the coefficient at 0 Hz, the DC-
 21 offset-will be greater than other values of \mathbf{F}_Φ , causing
 22 it to be selected as the dominant frequency. \mathbf{F}_Φ is
 23 the discrete Fourier transform of $\tilde{\mathbf{f}}_\Phi$: $\mathbf{F}_\Phi = \text{DFT}(\tilde{\mathbf{f}}_\Phi)$,
 24 where $\text{DFT}(\cdot)$ is the discrete Fourier transform, and
 25 k is the frequency index. The frequency index corre-
 26 sponding to the frequency with the most energy β is
 27 computed as follows:

$$\beta = \text{argmax}_k \|\mathbf{F}_\Phi(k)\| \quad (3)$$

28 where $\|\mathbf{F}_\Phi(k)\|$ is the magnitude of $\mathbf{F}_\Phi(k)$. Note that
 29 the frequency in Equation (3) is not the Nyquist rate.
 30 The Nyquist rate applies to sampling a continuous
 31 signal in order to accurately reconstruct that signal.

Algorithm 1 Computing the sampling rate for single segment/single apex

Input: I_Φ , the video segment. n_0 , midpoint-apex time point (if given). N , number of frames in Φ .

Output: I_{Φ^*} , downsampled video segment.

```

1: procedure DOWNSAMPLESEGMENT( $I_\Phi$ )
2:   for all frames  $n \in \Phi$  do
3:      $\Delta I_n \leftarrow$  optical flow from  $n - 1$  to  $n$ 
4:      $f(n) = \sum_{\mathbf{x}} \|\Delta I_n(\mathbf{x})\|_2$ 
5:   end for
6:    $\mathbf{f}_\Phi \leftarrow$  vector corresponding to all features  $f$ 
7:    $\bar{\mathbf{f}}_\Phi \leftarrow \mathbf{f}_\Phi - \text{mean of } \mathbf{f}_\Phi$ 
8:    $\mathbf{F}_\Phi \leftarrow$  Discrete Fourier transform of  $\bar{\mathbf{f}}_\Phi$ 
9:    $\beta \leftarrow \text{argmax}_k \|\mathbf{F}_\Phi(k)\|$ 
10:  if  $n_0$  is given then
11:     $\Phi_{\text{Apex}}^* \leftarrow \text{range } n_0 - \beta/2 < n \leq n_0 + \beta/2$ 
12:     $\Phi^* \leftarrow \Phi_{\text{Apex}}^*$ 
13:  else
14:     $M \leftarrow N/\beta$                                 ▷ (Downsampling factor)
15:     $\Phi^* \leftarrow \Phi \downarrow M$                             ▷ (Every  $M$ -th frame)
16:  end if
17:  return  $I_{\Phi^*}$ 
18: end procedure
    
```

In this paper we are downsampling a discrete signal by removing samples in the signal which have not changed much. For this reason, we sample at the dominant frequency itself.

The downsampling factor M is given by: (maximum frequency/dominant frequency). The frequency index β can be converted to the dominant frequency as: $2\pi\beta/N$. The maximum frequency index N corresponds to frequency 2π . It follows that: $M = N/\beta$. Let $\Phi^* = \Phi \downarrow M$. That is, Φ^* is every M -th frame of Φ . When the temporal feature has a high frequency, $\beta \rightarrow N$, the downsampling factor is near 1, and all of the frames are preserved. When the temporal feature has a low frequency, the downsampling factor increases, and most of the frames are removed.

3.2 Downsampling with Apex Labels

When apex label information is given, instead of segmenting the video evenly, the system segments the



Fig. 4: Comparison of sampling at even intervals versus sampling at the apex. A video is given, and its expression intensity is given. Sampling at even intervals retains frames that are further away from the apex. They are weakly expressed, and they are not a good representation of the emotion being expressed. Sampling at the apex retains the frames where the emotion is most strongly expressed.

1 video into durations centered at each apex. Instead
 2 of downsampling the segment evenly, the dominant
 3 frequency effects the duration of the segment. If the
 4 dominant frequency is high, then the method will
 5 select many frames at the apex; if low, only the frames
 6 nearest to the apex are selected. The human visual
 7 system has dynamic attention based on the changes of
 8 visual information. We realize attention as the number
 9 of selected frames. If there is not much change in the
 10 visual information, there is less attention given, and
 11 fewer frames are selected.

3.2.1 Time partitioning procedure

13 If apexes are provided, the video is partitioned into
 14 uniform segments of N frames, centered at the mid-
 15 point of the apex frames. There is a segment for
 16 each apex, and each segment is centered at that apex.
 17 Frames that are not near an apex will be removed. Let
 18 n_0 be the location of an apex. It now follows that:

$$\Phi_{\text{Apex}} = \{n : n_0 - N/2 < n \leq n_0 + N/2\} \quad (4)$$

19 Ordinarily we downsample the segment evenly.
 20 However, when apex labels are given we reformulate
 21 the downsampling method to take advantage of these
 22 labels. At the apex, the expressions are strong and the
 23 emotion is more easily detected. For this reason, the
 24 frames in the duration centered at the apex should be
 25 retained, rather than downsampling uniformly, which
 26 may retain frames further away from the apex where
 27 emotions are more difficult to detect. An example
 28 comparing sampling at a uniform rate versus sam-
 29 pling at the apex is given in Figure 4. There is no
 30 change in the way β is computed.

3.2.2 Downsampling the video segment

32 In this formulation, Φ_{Apex}^* varies in duration according
 33 to β , and is defined as follows:

$$\Phi_{\text{Apex}}^* = \{n : n_0 - \beta/2 < n \leq n_0 + \beta/2\} \quad (5)$$

34 If apex labels are given, Φ_{Apex}^* is taken to be Φ^* . When
 35 the temporal feature has a high frequency, N frames

are preserved and I_{Φ^*} is equivalent to $I_{\Phi_{\text{Apex}}}$. When
 the feature has a low frequency, the number of frames
 approaches 1, and most of the frames are removed.

3.3 Emotion Recognition System Pipeline

3.3.1 Face ROI extraction, registration and features

6 Faces are detected with a boosted cascade of Haar-
 7 like features [31]. If a face is not detected in the
 8 frame, we assign the expected label to that frame. For
 9 classification, we assign the class label that has the
 10 highest percentage of class occurrence. For regression,
 11 we assign the average value of the emotion intensity
 12 from the training data. A better method for assign-
 13 ing the label in this situation would be a first-order
 14 Markov assumption, but this is not the focus of work
 15 (see [35]). If ROI is detected, faces are registered with
 16 avatar image registration. The reader is referred to [24]
 17 for a more in depth explanation. We use Local Binary
 18 Patterns (LBP) because they are the most popular
 19 features in the field for representing a face. The reader
 20 is referred to [36], [37] for an in depth explanation. The
 21 features are computed for each frame in I_{Φ^*} .

3.3.2 Fusion

23 A method is needed to temporally fuse and smooth
 24 the estimated emotions. For each segment I_{Φ^*} , we
 25 propose fusing the *a posteriori* probabilities for each
 26 frame computed by the classifier. *A posteriori* probab-
 27 ilities are obtained with SVM [32]. The *a posteriori* probab-
 28 ilities are fused with combination-based match-
 29 score fusion [33], in which the scores, or *a posteriori*
 30 probabilities, from different matchers are weighted
 31 and combined to obtain a final, single score as the
 32 *a posteriori* probability. Let \mathbf{y}_j be the feature vector of
 33 LBP features of frame j in I_{Φ^*} . c_i is the class label from
 34 one of the classes: c_1, \dots, c_{n_c} . The estimated label for
 35 all the frames in I_{Φ^*} is \tilde{c} . Note that this assigns labels
 36 to all frames Φ , including those that were not selected
 37 for processing. Temporal smoothing is introduced by
 38 assigning all the frames in I_{Φ^*} the same label. $p(c_i | \mathbf{y}_j)$
 39 is the *a posteriori* probability of a class c_i . The first step

TABLE 2: Percentage of positively expressed affective dimension for the AVEC 2011 video sub-challenge.

Sets	Arousal	Expectancy	Power	Valence
Training	47	46	51	55
Develop	56	40	59	64

TABLE 3: Percentage of positively expressed AU for CK.

AU1	AU2	AU4	AU5	AU6	AU7	AU9
29.2	19.6	31.7	16.0	22.7	22.1	10.2
AU10	AU12	AU15	AU20	AU24	AU25	AU27
2.5	23.1	15.1	14.1	8.6	60.1	15.5

of fusion is estimation of $p(c_i|y_j)$ for each frame in I_{Φ^*} with the method in [38].

The second step aggregates the *a posteriori* probabilities from the selected frames into a single score. The classification rule for match-score fusion is:

$$\tilde{c} = \operatorname{argmax}_{c_i} h(c_i, \Phi^*, \mathbf{y}_1, \dots, \mathbf{y}_{n_f}) \quad (6)$$

where $h(\cdot)$ is the rule for aggregation, and n_f is the number of frames in Φ^* . The *Sum rule* is as follows:

$$h_{\text{Sum}}(c_i, \Phi^*, \mathbf{y}_1, \dots, \mathbf{y}_{n_f}) = \frac{1}{n_f} \sum_{j \in \Phi^*} p(c_i|y_j) \quad (7)$$

The *Product rule* is as follows:

$$h_{\text{Product}}(c_i, \Phi^*, \mathbf{y}_1, \dots, \mathbf{y}_{n_f}) = \prod_{j \in \Phi^*} p(c_i|y_j) \quad (8)$$

The *Min and Max rules* are as follows:

$$h_{\text{Min}}(c_i, \Phi^*, \mathbf{y}_1, \dots, \mathbf{y}_{n_f}) = \min_{j \in \Phi^*} p(c_i|y_j) \quad (9)$$

$$h_{\text{Max}}(c_i, \Phi^*, \mathbf{y}_1, \dots, \mathbf{y}_{n_f}) = \max_{j \in \Phi^*} p(c_i|y_j) \quad (10)$$

The *Mode rule* h_{Mode} , differs from the above rules by assigning the most common label to each frame in the segment.

The approach can be applied to regression by taking the result of the aggregation rule to be the final decision value. This replaces Equation 6, where a second classifier is applied:

$$\tilde{c}_{\text{Regression}} = h(c_i, \Phi^*, \mathbf{y}_1, \dots, \mathbf{y}_{n_f}) \quad (11)$$

Note that, for regression, we do not estimate the *a posteriori* probability. $p(\cdot)$ in the above equations is replaced with the decision values from SVR [32].

4 EXPERIMENTS

4.1 Datasets

AVEC 2011 [6] and 2012 [7] are grand challenge datasets. In this paper, they are used to compare the proposed method to other state-of-the-art methods. It is a non-trivial, unconstrained dataset: (1) the frame rate is too high to load all frames into memory. For example, if AVEC 2012 has 1351129 frames, if LBP features and baseline audio features [6] are used which have 7841 dimensions, and if double floating

TABLE 4: Percentage of classes for MMI-DB emotions.

Anger	Disgust	Fear	Happy	Sad	Surprise
21.1	13.9	13.0	19.7	14.4	17.9

points are used for each feature, it would require 8.48 GB to load all frames into memory. This exceeds the memory of most computers (88.9% of computers have up to only 8 GB of computer memory according to a recent hardware survey [39]). (2) The subjects are free to change pose, and use hand gestures, and (3) the videos are not acted. The videos are not pre-cut, and a person can express multiple emotions per video. In the AVEC datasets, a person is presented with the Sensitive Artificial Listener [40] who engages the person in conversation, and causes emotionally colored conversations by being biased to express a particular emotion, such as belligerence or sadness. Emotions expressed in this scenario are natural, continuous, and spontaneous. An example is available online [41]. In this example, a person is interacting with a specific character named Spike. Spike is confrontational, and aggravates the person during conversation. Note that the person is smiling, but not from being pleased. The smile is caused by the person being polite and exercising restraint in response to hostility. A separate classifier is used for each affect dimension (see Section 4.2).

The AVEC datasets are divided into three partitions: (a) 31 interviews of 8 different individuals form the *training* set. It is used as samples for a training model. (b) 32 interviews of 8 individuals, who are different from the training set form the *development* set. It is used as the testing fold in the training phase, and (c) 32 (AVEC 2012) or 11 (AVEC 2011) interviews of new individuals who are not in the development or training set form the *testing* set. The testing set is the official validation fold with which algorithms are compared to each other. The average length of all the videos in AVEC 2011 is $14.6 \times 10^3 \pm 5.20 \times 10^3$ frames. All results are given in terms of the frame level subchallenge. The percentage of positively expressed affective dimension for the training and development datasets for AVEC 2011 dataset are given in Table 2. The percentages for the testing set are not available because the labels are withheld by the challenge organizers.

The second dataset used is CK [3]. We use this database to test the quality of results of the proposed sampling method, when apex labels are provided. The length of segments range from 3 frames to over 100. The percent of positively expressed AU are given in Table 3. We follow the testing methodology in Koelstra et al. [15]. An AU is selected if it has more than 10 positive examples. We detect the following actions units (AU): {1, 2, 4, 5, 6, 7, 9, 10, 12, 15, 20, 24, 25, 27}. The reader is referred to Lucey et al. [3] for a more detailed expla-

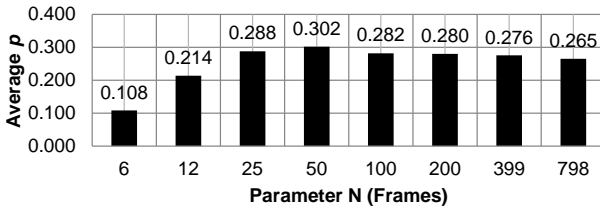


Fig. 5: Average correlation of all affect dimensions on development set, AVEC 2012 frame-level subchallenge for varying values of N .

nation of the data. We use leave-one-person-out cross-validation. A binary classifier is used for each AU.

MMI-DB [4] is frontal face video data similar to CK. For most videos, the emotion peaks near the middle of the video. The percentage of class for each emotion is given in Table 4. We use leave-one-person-out cross validation. We use all sessions that have emotion labels, and we consider the classes with at least 10 positive examples. We use only frontal faces. A multi-class classifier is used.

4.2 Expression and Emotion Labels

We use three labeling systems: action units [42], emotions based on the Ekman big six [42] and the Fontaine emotional model [43]. Expressions and emotions are not the same. Expressions are facial muscle movements. Ekman and Friesen [42] defined the minimal set of facial muscle movements, or action units (AUs), that are used in expressions. This is the Facial Action Coding System. Emotion differ from expressions in that they are the underlying mental states that may illicit expressions. A common system for discrete emotional states is the Ekman big six: happiness, sadness, fear, surprise, anger and disgust.

A different system for emotion labels is the Fontaine emotional model [43] with four affect dimensions: *valence*, *arousal*, *power* and *expectancy*. An emotion occupies a point in this four-dimensional Euclidean space. Valence, also known as evaluation-pleasantness, describes positivity or negativity of the person's feelings or feelings of situation, e.g., happiness versus sadness. Arousal, also known as activation-arousal, describes a person's interest in the situation, e.g., eagerness versus anxiety. Power, also known as potency-control, describes a person's feeling of control or weakness within the situation, e.g., power versus submission. Expectancy, also known as unpredictability, describes the person's certainty of the situation, e.g., familiarity versus apprehension. For a more detailed explanation, the reader is referred to [43]. With this system, multiple emotions can be expressed at the same time. An Ekman big six emotion [44] occupies a point in each of these four dimensions.

An expression or emotion also has intensity. It can be continuous, where the label has a numerical value representing its intensity, such as in AVEC 2012 [7].

The intensity can also be discrete, where the numerical values have been categorized into bins. In CK [3], an AU is either expressed (positive) or not expressed (negative). In AVEC 2011, the intensity was quantized into values higher than the average value (positive), or lower than the average value (negative). We use discrete action units for CK, discrete big six-based emotions for MMI-DB, discrete Fontaine for AVEC 2011 and continuous Fontaine for AVEC 2012.

Another system for level quantization has four states: neutral, onset, apex and offset [15]. These states indicate the intensity of an emotion, e.g., an expression is neutral when it has no expression, and an expression is at its apex when it has its greatest intensity. These four states form a state space. A person's expression will transition between these states, e.g. over time it will go from neutral to onset to apex.

4.3 Performance Metrics

The AVEC datasets have two scoring systems. In AVEC 2011 [6] the metrics are weighted accuracy (WA) and unweighted accuracy (UA). Weighted accuracy is the classification rate, and is also known as percent correct, calculated as follows:

$$WA = \frac{1}{n_c} \sum_{i=1}^{n_c} p(c_i) \frac{tp^i}{tp^i + fp^i} \quad (12)$$

where tp_i is the number of true positives of class i , fp_i is the number of false positives of class i , and n_c is the number of classes and $p(c_i)$ is the percentage of class. Unweighted accuracy is defined as:

$$UA = \frac{1}{n_c} \sum_{i=1}^{n_c} \frac{tp_i}{tp_i + fp_i} \quad (13)$$

This metric is used because some classes in the data have disproportionate percentage. For example, positive valence has a percentage of class higher than 60% in the training fold. The results for AVEC 2012 are given in terms of the Pearson product-moment correlation coefficient with the ground-truth labels. It is computed as:

$$\rho = \frac{E((\mathbf{c} - E(\mathbf{c}))(\hat{\mathbf{c}} - E(\hat{\mathbf{c}})))}{\sigma_c \sigma_{\hat{\mathbf{c}}}} \quad (14)$$

where $E(\cdot)$ is the mean, \mathbf{c} are the ground-truth labels across all persons and videos concatenated into a single vector. $\hat{\mathbf{c}}$ are the estimated labels across all persons and videos concatenated into a single vector; μ_c and $\mu_{\hat{\mathbf{c}}}$ are the mean of the ground-truth and predicted labels, respectively; and σ_c and $\sigma_{\hat{\mathbf{c}}}$ are the standard deviation of the ground-truth and predicted labels, respectively. CK comparisons are quantified with the F_1 measure [15]:

$$F_1 = 2 \left(\frac{(\text{precision})(\text{recall})}{\text{precision} + \text{recall}} \right) \quad (15)$$

TABLE 5: Weighted Accuracy Results for Various Sampling Methods, Registration Methods and Fusion Methods for AVEC 2011 Development set. Sampling: sampling rate. Uniform: uniform number of frames. Reg: registration method. AIR: avatar image registration. RST: similarity transform. Rule: fusion rule. HMM: hidden Markov model. WA: weighted accuracy.

Sampling	Reg	Rule	WA Result				
			Aro	Exp	Pow	Val	Avg
Proposed	AIR	Sum	71.7	62.1	63.4	65.3	65.6
Proposed	AIR	Max	71.0	60.7	63.2	64.8	64.9
Proposed	RST	Min	70.1	61.0	62.1	65.0	64.5
Proposed	RST	Mode	71.0	61.9	61.8	62.6	64.3
Proposed	RST	Sum	70.7	60.2	63.0	63.0	64.2
Proposed	RST	Prod	69.6	61.9	61.2	62.8	63.9
Proposed	RST	Max	69.0	60.1	61.6	64.6	63.8
Proposed	AIR	HMM	68.5	62.0	59.8	64.9	63.8
Proposed	AIR	Prod	70.2	59.8	60.5	64.3	63.7
Proposed	AIR	Mode	71.6	59.5	60.9	62.6	63.6
Proposed	RST	No	69.0	59.6	62.1	63.6	63.6
Proposed	AIR	Min	70.1	59.2	60.8	62.6	63.2
Proposed	AIR	No	69.1	55.5	62.5	64.7	62.9
Uniform 3	AIR	Sum	69.3	57.7	61.0	63.7	62.9
Uniform 6	AIR	Sum	67.7	60.0	57.9	62.9	62.1
Uniform 9	AIR	Sum	67.6	57.2	60.2	61.4	61.6
Uniform 6	AIR	Mode	67.9	56.7	58.7	62.3	61.4
Uniform 3	AIR	Mode	65.9	61.6	59.0	58.5	61.2
Uniform 9	AIR	Mode	68.3	55.6	58.8	58.6	60.3
Uniform 1	AIR	No	65.0	56.3	57.0	62.4	60.2

1 It is the harmonic mean of precision and recall. It
 2 can be more meaningful in cases of disproportionate
 3 percentage of different classes.

4.4 Parameters

5 After ROI extraction, all face images are resized to
 6 200×200 with bicubic interpolation. For avatar image
 7 registration, we train the avatar reference image from
 8 the development data subsampled at 12 fps. The
 9 parameters specific to avatar image registration are:
 10 $\alpha = 2$, $1/(\sigma)^2 = .005$, and the number of iterations
 11 is 3. All three of these parameters are empirically
 12 selected from the previous work [24]. The parameters
 13 specific to LBP [26] are: the number of local regions is
 14 8, patterns are computed for 8 neighbors at a radius of
 15 1, and there are 10×10 sub-regions on the entire face
 16 image. All classifiers are SVM [32]. The parameters
 17 specific to the SVM are: an RBF kernel is used, the cost
 18 $c = 1$, and $\gamma = 2^{-8}$. The feature vectors are normalized
 19 to $[-1, 1]$. For regression, an ϵ -SVR is used [32]. The
 20 parameters specific to the regressor are: $\epsilon = 0.1$.

21 N is the initial number of frames. There should
 22 be enough frames in Φ to describe the expression
 23 in progress. In the unconstrained case, an expression
 24 can be very quick. If that expression were a microex-
 25 pression, it could be as fast as $1/25$ th of a second,
 26 requiring 25 fps [45]. MMI-DB videos were captured
 27 at 24 fps, so we recommend that $N > 24$ for MMI-DB.
 28 We chose $N = 50$ frames. It is validated empirically.
 29 AVEC 2012 is used for selecting parameter N . A value
 30 is selected empirically by varying N in powers of 2
 31 seconds: $\{2^{-3}, \dots, 2^8\}$. The results are given in Figure

TABLE 6: Confusion Matrices for MMI-DB. An: anger. Di: disgust. Fe: fear. Ha: happiness. Sa: sadness. Su: surprise.

(a)

Yang and Bhanu [24]						
	An	Di	Fe	Ha	Sa	Su
An	71.7	2.2	2.2	6.5	4.4	13.0
Di	12.9	48.4	16.1	6.5	0.0	16.1
Fe	27.6	0.0	58.6	3.5	0.0	10.3
Ha	9.5	0.0	4.8	76.2	0.0	9.5
Sa	25.0	0.0	6.3	6.3	59.4	3.1
Su	18.4	2.6	7.9	0.0	5.6	65.8

(b)

Uniform Sampling of 1 Frame						
	An	Di	Fe	Ha	Sa	Su
An	76.4	4.7	6.8	2.2	2.2	8.7
Di	9.7	64.5	9.7	3.2	3.2	9.7
Fe	24.1	0.0	55.2	0.0	6.9	13.8
Ha	11.9	0.0	2.4	76.2	2.4	7.1
Sa	28.1	0.0	6.3	3.1	53.1	9.4
Su	21.1	7.9	5.3	0.0	0.0	65.8

(c)

Proposed with Frame Differencing as Temporal Feature						
	An	Di	Fe	Ha	Sa	Su
An	78.3	6.5	0.0	4.4	4.4	6.5
Di	9.7	67.7	12.9	0.0	0.0	9.7
Fe	27.6	0.0	58.6	3.5	0.0	10.3
Ha	14.3	7.1	9.5	61.9	0.0	7.1
Sa	21.9	0.0	6.3	0.0	62.5	9.4
Su	15.8	2.6	2.6	0.0	2.6	76.3

(d)

Proposed with Dense-SIFT as Temporal Feature						
	An	Di	Fe	Ha	Sa	Su
An	76.1	6.5	0.0	0.0	4.4	13.0
Di	9.7	58.1	16.1	3.2	0.0	12.9
Fe	17.2	0.0	69.0	3.5	0.0	10.3
Ha	14.3	4.8	2.4	69.1	0.0	9.5
Sa	21.9	3.1	0.0	3.1	59.4	12.5
Su	18.4	0.0	2.6	0.0	0.0	79.0

(e)

Proposed with Optical Flow as Temporal Feature						
	An	Di	Fe	Ha	Sa	Su
An	73.9	4.4	4.4	0.0	8.7	8.7
Di	6.5	74.2	6.5	0.0	0.0	12.9
Fe	17.2	3.5	69.0	0.0	0.0	10.3
Ha	9.5	4.8	2.4	76.2	0.0	7.1
Sa	21.9	0.0	0.0	3.1	71.9	3.1
Su	21.1	2.6	5.3	2.6	2.6	65.8

TABLE 7: Weighted accuracy and unweighted accuracy on MMI-DB for varying temporal features. Prop.: Proposed. UA: unweighted accuracy. WA: weighted accuracy.

Method	WA	UA
Yang and Bhanu [24]	63.4	64.8
Uniform Sampling of 1 Frame	65.2	66.6
Prop. + Frame Differencing Temporal Feature	67.6	68.4
Prop. + Dense-SIFT Temporal Features	68.4	69.4
Prop. + Optical Flow Temporal Feature	71.8	72.0

5. $N = 50$ gives the best performance. It decreases
 as N is reduced below 50 frames. For decreasing
 values of N , the upper bound of β decreases,
 and more frames will be forced to be selected. The worst
 performer is 6 frames per segment.

4.5 Experimental Results

Training results that select the best performing com-
 bination of registration method and fusion rule are

TABLE 8: Comparison to Other Methods on AVEC 2011 Frame-level Subchallenge Testing Set. Bold indicates best performer, underline indicates second best.

(a) Development Set										
Method	Arousal		Expectancy		Power		Valence		Average	
	WA	UA	WA	UA	WA	UA	WA	UA	WA	UA
Proposed Method	71.7	67.8	62.1	59.8	63.4	61.8	65.3	60.7	65.6	62.6
Glodek et al. [13]	58.2	53.5	53.6	53.2	53.7	53.8	53.2	49.8	54.7	52.6
Dahmane and Meunier [8]	54.9	55.0	51.8	51.2	53.2	52.8	56.6	55.5	46.6	53.6
Baseline [6]	<u>60.2</u>	<u>57.9</u>	<u>58.3</u>	<u>56.7</u>	<u>56.0</u>	52.8	<u>63.6</u>	60.9	<u>59.5</u>	<u>57.1</u>

(b) Testing Set										
Method	Arousal		Expectancy		Power		Valence		Average	
	WA	UA	WA	UA	WA	UA	WA	UA	WA	UA
Proposed Method	56.5	56.9	59.7	55.1	48.5	49.4	59.2	56.7	56.0	54.5
Glodek et al. [13]	56.9	57.2	47.5	47.8	47.3	47.2	55.6	55.6	51.8	52.0
Dahmane and Meunier [8]	63.4	63.7	35.9	36.6	41.4	41.1	53.4	53.6	48.5	48.8
Baseline [6]	42.2	52.5	<u>53.6</u>	<u>49.3</u>	36.4	37.0	52.5	51.2	46.2	47.5

TABLE 9: Comparison to Other Methods on AVEC 2012 Video-based Frame-level Subchallenge Testing and Development Sets. Bold indicates best performer, underline indicates second best. Aro: arousal. Exp: expectancy. Pow: power. Val: valence. Avg: average of all.

Video-only Development Set					
Method	Aro	Exp	Pow	Val	Avg
Baseline [7]	0.151	0.122	0.031	0.207	0.128
Proposed Method	0.379	0.199	<u>0.244</u>	0.385	<u>0.302</u>
Nicolle et al. [18]*	0.354	0.538	0.365	0.432	0.422
Ozkan et al. [19]	0.117	0.076	0.062	0.200	0.114
Savran et al. [21]	0.306	<u>0.215</u>	0.242	0.370	0.283
Yang and Bhanu [24]	0.173	0.099	0.164	0.198	0.159

Video-only Testing Set					
Method	Aro	Exp	Pow	Val	Avg
Baseline [7]	0.077	0.128	0.030	0.134	0.093
Proposed Method	0.302	0.244	0.199	0.279	0.252
Nicolle et al. [18]**	-	-	-	-	-
Ozkan et al. [19]**	-	-	-	-	-
Savran et al. [21]	<u>0.251</u>	<u>0.153</u>	0.099	0.210	0.178
Yang and Bhanu [24]	0.190	0.105	<u>0.142</u>	0.177	0.154

*Best performing video feature.

**Video-only testing set not reported.

given in Section 4.5.1. Results comparing temporal feature methods on MMI-DB are given in Section 4.5.2. Testing results on AVEC 2011 and AVEC 2012 are given in Section 4.5.3. Testing results on CK are given in Section 4.5.4. A discussion on memory cost and visual examples of the proposed downsampling method are given in Section 4.5.5.

4.5.1 Selection of registration method and fusion rule

The selection of the best performing combination of registration method, and fusion rule is made with the development set on AVEC 2011. This experiment also tests the performance gain when using the proposed method versus a uniform sampling rate. The results for different registration techniques, sampling methods, and rules are given in Table 5. The methods are ranked in descending order of average performance across all four classes. Under sampling method, Uniform indicates that a uniform number of frames were selected for each segment, Proposed indicates that the proposed method was used. RST indicates that a similarity transform was used with eye points as

control points. Sum refers to the sum rule; Product, product rule; Min, min rule; Max, max rule; Mode, the mode rule; and no fusion, the labels are assigned without any fusion. HMM indicates hidden Markov model fusion detailed in [47].

The best performer (Proposed + AIR + Sum) improves classification rate by 5.4% versus Uniform 1 + AIR + No fusion. This is the combination that is used in the following experiments, except for AVEC 2011 testing results, which are the original, official entry results of the challenge that used the Max rule. The combinations can be grouped into three categories: (1) dynamic downsampling with avatar image registration, (2) dynamic downsampling with similarity transform based registration, and (3) uniform downsampling with avatar image registration. It is clear that methods with the proposed dynamic sampling rate (groups 1 and 2) are better than methods that sample uniformly (group 3). While the two best performers use AIR registration, the difference between avatar image registration (group 1) and similarity transform registration (group 2) is not as clear. Replacing avatar image registration with similarity registration does not cause a significant drop in performance. Proposed + AIR + Sum and Proposed + RST + Sum have a difference of 1.4% on the average. For AVEC 2011, we conclude that intelligent selection of frames is a greater contributor to classification rate than a better registration algorithm.

4.5.2 Evaluation of temporal feature

We evaluate the use of optical flow as a temporal feature versus SIFT flow and frame differencing with MMI-DB empirically in Table 6. Weighted and unweighted accuracies are given in Table 7. When using a different temporal feature, ΔI_n is replaced by the new method (frame differencing or dense SIFT), the L_2 -norm of the difference between frames n and $n - 1$ is still used. For uniform sampling of 1 frame, the frame at the apex is the only frame used. Yang and Bhanu [24] is the worst performer because it uses all the frames, including the frames furthest away from

TABLE 10: Apex label results compared to other methods for 14 AUs on CK. Bold indicates best F_1 performance, underline indicates second best. Avg: Average of all AUs.

Method	Facial Action Unit														Avg.
	1	2	4	5	6	7	9	10	12	15	20	24	25	27	
Proposed	85.3	93.0	87.7	69.6	90.5	<u>62.4</u>	68.5	43.5	76.9	71.0	<u>74.0</u>	65.2	93.6	84.2	76.1
Koelstra et al. [15]	<u>86.8</u>	90.0	73.1	80.0	80.0	46.8	77.3	<u>48.3</u>	<u>83.7</u>	<u>70.3</u>	79.4	<u>63.2</u>	95.6	<u>87.5</u>	<u>75.9</u>
Valstar et al. [46]	87.6	94.0	<u>87.4</u>	<u>78.3</u>	<u>88.0</u>	76.9	<u>76.4</u>	50.0	92.1	30.0	60.0	12.3	<u>95.3</u>	89.3	<u>72.7</u>
Yang and Bhanu [24]	82.0	92.1	82.0	<u>58.6</u>	84.9	52.5	68.4	34.8	68.2	66.7	65.7	51.1	85.6	67.2	68.6

the apex. Frame differencing is the fastest method for computing the temporal feature, but it has the worst performance among other temporal features. SIFT flow improves performance, but it is the slowest temporal feature optical flow has a better performance and speed. Retaining only 1 frame is worse than the proposed downsampling method. We conclude that, for MMI-DB, there are instances where retaining more than 1 frame can improve classification rate, if those frames are intelligently selected.

4.5.3 Results without apex labels

Results on the official AVEC 2011 testing and development sets are given in Table 8. The proposed method is compared to the two other entries that employed a dynamic sampling rate and it is always the best or second best performer for the development set. On the testing set, it improves weighted accuracy by 9.8%, and unweighted accuracy by 7.0% over the baseline approach. In [8], the method pays more attention when the predicted label changes, which assumes that the prediction is accurate, which is not always the case, especially for a difficult dataset such as AVEC 2011. We believe that the proposed method does well because it is the only downsampling method based on changes of visual information of the face.

Results on AVEC 2012 frame-level subchallenge are given in Table 9. Yang and Bhanu [24] is similar to the proposed approach but does not incorporate a downsampling and uses LPQ features. For the development set, Nicolle et al. [18] has the best performance, but they did not provide video-only testing results. They noted that the ground-truth labelers had a time delay when recording the label, and they incorporated meta-data of who the user was speaking with, e.g. if the embodied agent speaking to them was belligerent. Though this improved performance, it is ad hoc in the sense that rater time delay may be specific to AVEC 2012, and meta-data about who the person is speaking to may not be available with other datasets.

4.5.4 Results with apex labels

The efficacy of the proposed method with apex labels on CK is given in Table 10. A comparison is made with other methods according to F_1 measure. For in-depth results see [35]. Yang and Bhanu [24] method does not take advantage of apex frame labeling. The proposed method takes advantage of apex labelling and it performs better. We performed best for 4 AUs. Valstar

TABLE 11: Summary of Frames Used for Each Dataset. Bold indicates least memory cost in terms of frames, underline indicates second best.

	AVEC 2011	AVEC 2012	CK	MMI-DB
# of Videos	74	95	488	222
# of Frames	1090476	1351129	8795	23466
Proposed	<u>65871</u>	<u>76960</u>	1536	764
Dahmane [8]	196051	239920	-	-
Savran [21]	-	232600	-	-
Glodek [13]	740	950	<u>4930</u>	<u>2220</u>

and Pantic [48] perform best for 6 AUs. However, the proposed method has a higher average F_1 measure among all the other works. Results for varying fusion rules, sampling methods and registration methods are given in [35]. The comparison to [24] demonstrates the importance of incorporating temporal information. Intuitively, assuming that each frame is equally discriminative, selecting as many frames as possible, such as in Yang and Bhanu [24], should increase the true positive rate by introducing more samples for the fusion. However, samples that are further away from the apex contain less relevant information of the expression being captured. Frames further away from the apex are close to neutral. They are not good examples of the expression being expressed, and they reduce accuracy. The proposed method sampled frames at the apex, and Koelstra et al. [15] modelled the temporal phases including the apex, this may explain the gap in performance.

4.5.5 Memory cost savings and temporal feature results

In the following, we discuss the memory cost saving for each dataset, and show examples of the temporal feature. For AVEC 2011, the total number of frames for the development, training and testing (video subchallenge) partitions are {449074, 501277, 140125}, respectively. The proposed method downsampled the number of frames by a factor of 16.6, retaining {27412, 30076, 8383} frames. For CK, the proposed method sampled 3.4 ± 2.2 frames. For MMI-DB the proposed method sampled 3.4 ± 1.5 . A comparison of the number of frames reduced by the proposed method is given in Table 11.

For a detailed explanation of the downsampling methods for related work, see Section 2.2. Because the method in [21] retains outliers based on the regression label, it can only be applied to continuous

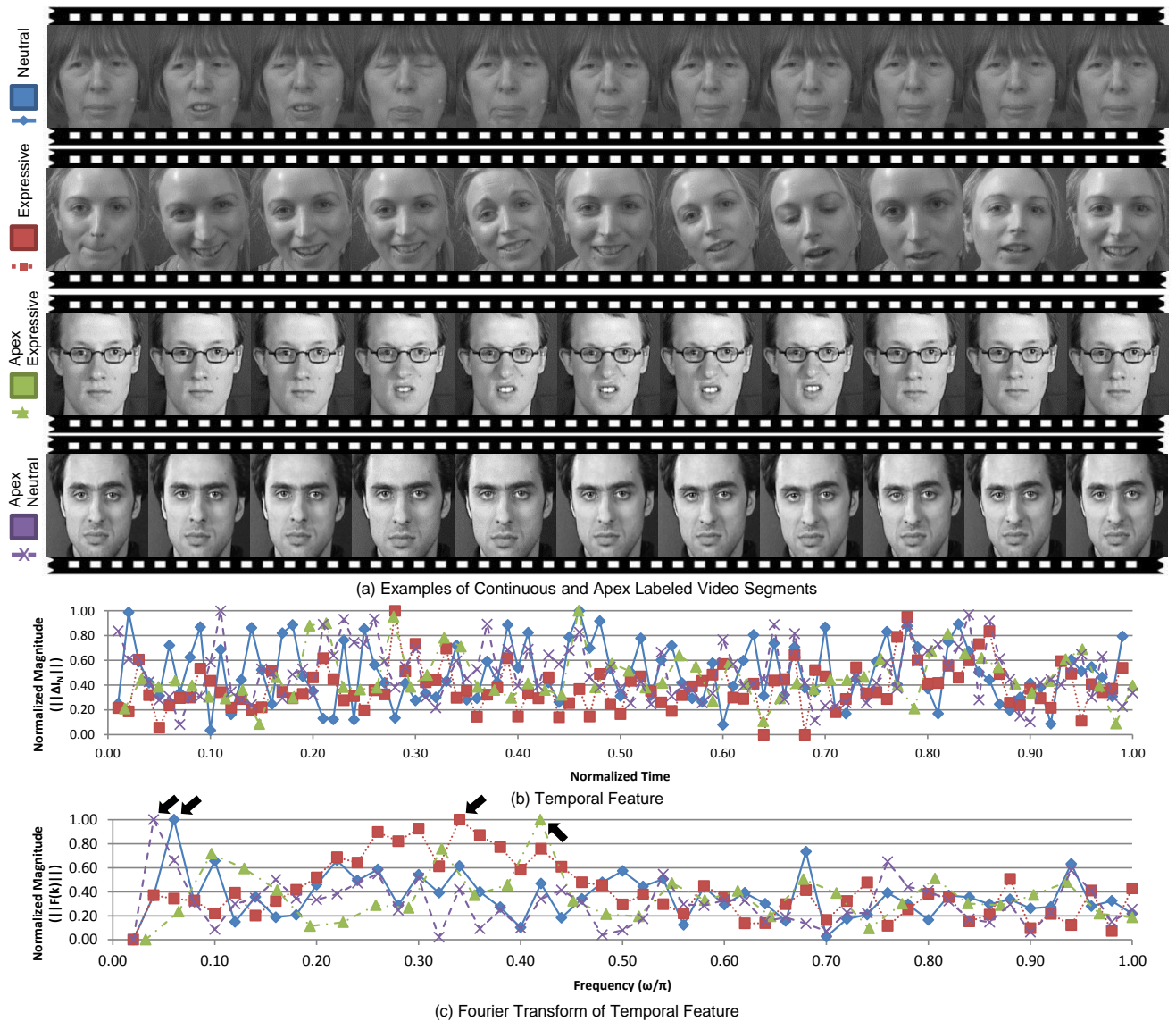


Fig. 6: (a) From top to bottom, a continuous video segment of a neutrally expressive person; a continuous video segment of an expressive person; an apex segment of a person who is expressive; an apex segment of a person who is less expressive. (b) The temporal feature of each of the examples, and (c) the discrete Fourier transform of the temporal feature. Note that both the continuous neutral and apex labeled less expressive examples have a low dominant frequency, whereas the other two expressive examples have a higher dominant frequency. Black arrow indicates dominant frequency.

1 label intensities, such as in AVEC 2012. The method
 2 would process each testing frame uniformly. In [8],
 3 for continuous data, we categorized the labels into 10
 4 bins. This method is not applicable to apex labeled
 5 data, where the videos are segmented and have a
 6 single class label. In [13], frames are sampled uni-
 7 formly. The method's memory cost is proportional to
 8 the number of videos, so the method does not reduce
 9 memory cost well for datasets with many videos, such
 10 as CK and MMI-DB. Though the method has the least
 11 number of frames for AVEC 2011 and AVEC 2012, it
 12 may sample the long videos too sparsely to precisely
 13 detect when emotion changes. The proposed method
 14 can be used to reduce the number of frames on all
 15 four datasets, both on continuous and discrete data,

and on segmented and unsegmented data. It is the
 the best or second best method for reducing memory cost
 on all four datasets.

A detailed example of two continuous video seg-
 ments from AVEC 2012, and two apex labeled seg-
 ments from MMI-DB is given in Figure 6. The mag-
 nitude has been normalized to provide a better un-
 derstanding of the results. The time range has been
 normalized because MMI-DB segments are of differ-
 ent lengths. For the discrete Fourier transform, the
 frequency is normalized to [0, 1]. The first example
 in Figure 6(a) is of a person who does not use many
 expressions (Neutral). In this case the dominant fre-
 quency is at .06 cycles/frame, so only a few frames
 would be selected. The second row is of a person

1 who is using many expressions and changing her pose
2 (Expressive). Intuitively, many frames will be required
3 to describe this segment, which is corroborated by the
4 dominant frequency being at .34 cycles/frame. The
5 third row is of a person who holds his expression for
6 a long time at the apex (Apex Expressive). The domi-
7 nant frequency is at .42 cycles/frame. In this example,
8 there are 62 frames in the cycle, thus $.42 \times 62 \approx 26$
9 frames would be selected. It can be observed from the
10 example frames that his expression is held at the apex
11 for roughly half of the frames, corroborating keeping
12 26 of the 62 frames. The fourth row is of a person who
13 weakly expresses his emotion (Apex Neutral). In this
14 case, the dominant frequency is .04 cycles/frame, so
15 very few frames would be selected.

5 CONCLUSIONS

17 In this paper, vision and attention theory was em-
18 ployed to temporally downsample the number of
19 frames for video-based emotion and expression recog-
20 nition. It was found that a uniform frame rate de-
21 creases performance and can unnecessarily increase
22 memory cost for high frame rates. With the proposed
23 method, AVEC 2011 is downsampled by a factor of
24 16.6 and weighted accuracy is improved over the
25 baseline approach by 9.6% on the testing set. AVEC
26 2012 is downsampled by a factor of 17.6 and corre-
27 lation is improved over the baseline by .159 on the
28 testing set. CK is downsampled by a factor of 5.72 and
29 the F_1 measure is improved by 0.3. MMI-DB dataset
30 is downsampled by a factor of 30.1 respectively and
31 weighted accuracy is increased over [24] by 8.4%
32 for all sessions. Unlike previous works, we reported
33 results on all four datasets.

34 The conventional process of using a short dura-
35 tion of frames centered at the apex was corroborated
36 with the proposed sampling method, and extended
37 to allow for an increase in duration when appropri-
38 ate. It was found that top methods from previous
39 challenges [24] did not generalize to continuous data
40 sets. In that challenge, registration was found to be
41 a significant contributor to performance, whereas, in
42 the AVEC datasets, we have found that registration
43 does not significantly contribute to performance. Pre-
44 vious datasets were segmented to the time points of
45 most significance, and we posit that, for continuous
46 datasets, a method must be critical in its selection
47 of frames. A limitation of the current work is that
48 the frames are processed in evenly sized segments,
49 which may cause a boundary effect if an unlabeled
50 apex is close to the segmentation boundary. However,
51 this can be addressed by using overlapped boundary
52 segments.

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expression recognition.

Albert C. Cruz received the BS degree in electrical engineering from the University of California, Riverside, CA, USA in 2008. He is currently a PhD student in Electrical Engineering at the Center for Research in Intelligent Systems at the University of California, Riverside, CA, USA. His research interests include image processing, computer vision, pattern recognition and machine learning. His current research focuses on biologically-inspired algorithms for facial emotion and



Bir Bhanu received the SM and EE degrees in electrical engineering and computer science from the Massachusetts Institute of Technology, Cambridge, the PhD degree in electrical engineering from the Image Processing Institute, University of Southern California, and the MBA degree from the University of California, Irvine. He is a distinguished professor of electrical engineering and a cooperative professor of computer science and engineering, mechanical engineering, and bioengineering, and the director of the Center for Research in Intelligent Systems and the Visualization and Intelligent Systems Laboratory at the University of California, Riverside. He is also the director of NSF IGERT on Video Bioinformatics at UCR. His research interests include computer vision, pattern recognition and data mining, machine learning, artificial intelligence, image processing, image and video database, graphics and visualization, robotics, human-computer interactions, biological, medical, military, and intelligence applications. He has been the principal investigator of various programs for the NSF, DARPA, NASA, AFOSR, ARO, ONR, and other agencies and industries. He is a fellow of the IEEE, AAAS, IAPR, and SPIE.



disparity segmentation, and structure-and-motion segmentation.

Ninad S. Thakoor received the B.E. degree in electronics and telecommunication engineering from the University of Mumbai, Mumbai, India, in 2001 and the MS and PhD degrees in electrical engineering from the University of Texas at Arlington, TX, USA, in 2004 and 2009, respectively. He is a Post-doctoral Researcher with the Center for Research in Intelligent Systems, University of California, Riverside, CA, USA. His research interests include vehicle recognition, stereo