Modeling an Infinite Emotion Space for Expressionistic Cartoon Face Animation

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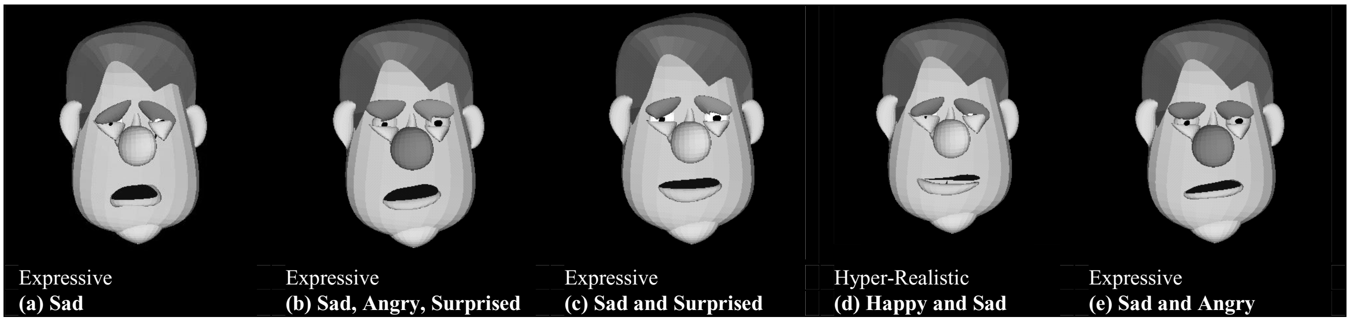

Figure 1: Selected results from a prototype of the proposed expression synthesis model for cartoon face animation. Row 1 shows instances of an example face model (17 Bezier patches). Row 2 delineates the degree of realism intended when invoking the corresponding expression in the emotion space (please see figure 2). Note the intentional change in eye and nose color due to anger.

Abstract

Inspired by traditional expressive animation, we attempt to propose an infinite emotion-space as a model to control free-form facial expression synthesis. Although a number of models already exist for capturing, synthesizing, learning and retargeting facial expressions, very few of them actually focus on modeling the emotion-space itself. Most of these models span a finite set of captured/created expressions, and apply model-space affine transformations to retarget them, or obtain new ones. We consider the fact that in reality any expression essentially originates in the emotion space (the brain), which eventually manifests itself as a group of transformations or interactions of physical body structures (bones, tendons, muscles, skin layers, etc.). In this light, we present an infinite emotion space model for syntheses of an infinite range of expressions for facial animation, limited only by the creativity and imagination of an animator.

CR Categories: I.3.5 [Computer Graphics]: Computational Geometry and Object Modeling – surfaces and object representations.

Keywords: Facial Animation, Modeling Emotion Space, Human Computer Interaction, Cartoon Animation.

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1 INTRODUCTION

Facial animation has been a subject of interest in the computer graphics research community for almost three decades now. Pioneered by Frederic I. Parke in 1972 [21], it has been driving research and efforts in numerous areas of application, e.g., virtual characters (avatars), human computer interaction, cognitive sciences, cosmetic surgery planning, computer games, and most of all, computer-generated animation. Depending upon the application area, various approaches have been taken to model the human face and its muscular and dermal behavior in pursuit of capturing and synthesis of realistic facial expressions. The FACS system [9] was probably one of the earliest attempts to identify and describe facial expressions in the form of discrete metrics (Action Units or AUs). Since then, many variations of the method have been explored to enable reliable coding and recognition of primary expressions and synthesis of novel ones in an expression space [1, 2, 7, 8, 12, 14, 20].

Such systems employ factorization (statistics), principle component analysis (PCA), or artificial neural networks (Artificial Intelligence) as rule-based approaches for modeling a facial expression space. Most of them focus on the expression coding and recognition sub space of the latter, and very few of them actually address the issue of modeling the expression space itself to provide a wider possible expression range for aesthetic facial animation [5]. Even those, that do address this issue, focus primarily on expression space, and very few of them actually attempt to model the emotion space itself [12, 22, 23, 24].

Surprisingly, there have already been a few noteworthy efforts in the cognitive sciences and psychology research community that actually attempt to model emotion space and explore its mapping with expression space [22, 23, 24]. An example publication describes a 2D facial expression space presented by Schlosberg [24]. But this theory, which was later extended by Russell [22], does not necessarily support realistic expressions when multi-dimensional scaling is used, because it uses only 6 primary expressions [12]. We attempt to employ the extensive research and knowledge already present in cognitive science [6, 12, 22, 23, 24, 26] as well as computer science [5, 8, 10, 11, 13, 14, 15, 16, 17, 18, 19, 21, 25] towards modeling an intuitive expression synthesis system for cartoon animation.

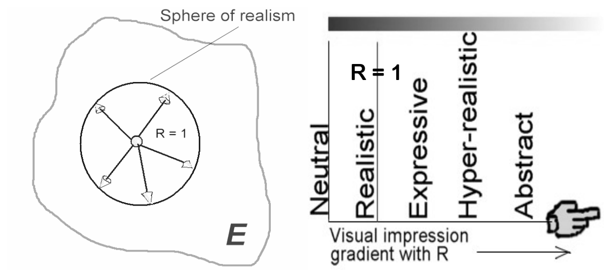
We consider the fact that an expression essentially originates in a virtual emotion space, which eventually manifests as a group of affine and/or non-rigid transformations of body parts or interactions of physical body structures (bone, tendon, muscle, skin layers, etc.). Most often this is in response to an observation through one of the body senses, or even thoughts (the reverse transformation mapping **H**). We thus aim at:

- Modeling a generalized emotion space **E** as a source of expression vectors for arbitrary cartoon face models; and

- Derive a mapping **G** from this model **E** to an infinite expression space **P** spanning visual impressions from abstract art (abstract) to real life imagery (realistic), traditional animation (expressive), and caricature (hyper-realistic).

1.1 The Concept

Consider a face model **M** defined by a set of discrete vertices **V**, where $\mathbf{V} = \{\mathbf{v}_i \mid \mathbf{v}_i \in \mathbf{R}^3; i \in \Gamma^+; 0 < i \leq n\}$. **V** can represent either the vertices of a manifold surface mesh with a connectivity $\mathbf{\Phi}$, the control points of an analytical surface defining **M,** or control elements of a synthetic anatomical structure modeling **M** (e.g. muscle model, spring model, etc.). We associate two regimes with **M**: an emotion space **E**, and an expression space **P**. We define a one-to-many mapping $\mathbf{G: E \rightarrow P}$. **G** maps an arbitrary emotion vector $\mathbf{e}_i$ to a set of expression vectors $\{\mathbf{p}_{ik} \mid \mathbf{p}_i \in \mathbf{R}^3; k \in \Gamma^+; 0 < k \leq m_i\}$. To map an expression from a weighted combination $\mathbf{e}^f$ of one or more emotion vectors to **M**, we obtain the corresponding set of expression vectors using **G**. This set of expression vectors can then be used to apply geometric transformations on **V** to obtain the desired visual effect in the object space. Later in this paper, we show that a barycentric combination of emotion vectors induces expressions in the realm of 'realism'. For all other combinations that do not satisfy this condition, expressions with visual impressions ranging from neutral to expressive to hyper-real to distorted are obtained.



(a) (b)

Figure 2: (a) The *sphere of realism** in emotion space. It is a sphere of unit radius, which defines the boundary of 'realism' the associated expression space. Any emotion vector $\mathbf{e}_i$ that lies outside this sphere would transform to the visual impression of a 'hyper-realistic' expression in the expression space. (b) Effect of change in magnitude of an emotion vector in **E** on visual impression of a face model mapped with the corresponding expression in **P**. **This term is meaningful only for an emotion vector space of dimensionality 3. It would be relatively more difficult to visualize a space of higher dimensions, and thus an example vector space of dimensionality 3 has been chosen to explain the conceptual relationships (please see section 3 for a detailed discussion).*

2 PRIOR WORK

The area of expression coding and recognition has witnessed extensive efforts towards modeling of human the expression space. The FACS system [9] is probably one of the earliest attempts to identify, elaborate and classify facial expressions in the form of atomic Action Units (AUs). It functions very well as a static technique for coding and recognizing expressions. However, it has limitations as a synthesis tool for novel expressions. The limitations arise from the fact that an expression lasts for a finite temporal period, and also varies in degree or amplitude based on a neutral expression over both time and space. Attempts to add a temporal dimension to the original FACS model have not been accepted widely, because still the model cannot provide a flexible and free form synthesis space for new expressions [20].

Other approaches have been presented to emphasize novel expression synthesis (conceptually analogous to motion-capture and synthesis). But most of them are rule-based [3, 7, 8, 11, 16], and thus the synthesis capabilities are limited by the behavior of the underlying models.
Recently, Noh et al. [19] proposed a novel technique to clone expression vectors and to automatically map them on arbitrary face models within constraints. This concept of synthesizing, storing, and reusing expressions is an important leap towards generality in expression space. However, the main focus of this work is on providing a framework for reusability of captured expressions; and

little details are given about actual synthesis of new expressions.

Another recent work by Chuang et al. [5] addresses the issue of adding flexibility to synthesis of novel expressions besides retargeting the captured expressions. The method extracts expression content from a sequence of images, and uses it to synthesize new expressions. This method provides both the expressionism of an expressive animation system, as well as the flexibility of a rule-based expression-coding system. However, it functions primarily in expression space unlike our proposed infinite emotion space model. Also the target face models in the aforementioned work are 2D image space elements as opposed to a general 3D shape representation in our method.

We present a continuous and infinite emotion space model for syntheses of neutral, through realistic, to very expressive and hyper-realistic (exaggerated and sometimes distorted) expressions for facial animation. We attempt to amalgamate the freedom of expression of traditional animation art with the generality of a realistic expression synthesis model for synthesis of unlimited re-usable expressions for cartoon face animation. The result is an infinite range of expressions that are limited only by the creativity and aesthetic sense of an animator.

3 THE INFINITE EMOTION SPACE

An essential contribution of this paper is a mathematical description of an infinite emotion space model. We define **E** as an N-dimensional emotion vector space spanning $\{\mathbf{e}_i \mid \mathbf{e}_i \in \mathbf{R}^N, |\mathbf{e}_i| = R\}$ when N tends to infinity. **E** is thus composed of two disjoint sets of emotion vectors:

- $\mathbf{E}_B = \{\mathbf{e}_{Bi} \mid R = |\mathbf{e}_B| = 1\}$, the set of basis emotion vectors, $\mathbf{E}_B \neq \mathbf{Ø}$.
- $\mathbf{E}_S = \{\mathbf{e}_{Si}\}$, the set of synthesized emotion vectors.

It is to be noted that the absolute orientations of $\mathbf{e}_i$ in **E** are of no practical significance, but their relative orientations are (since $\mathbf{e}_{Bi}$ are linearly independent and mutually orthogonal). The most intuitive way of visualizing an example emotion vector space of dimensionality N=3 ($\mathbf{E}^3$) is as a polar coordinate space with origin represented as a neutral emotional state $\mathbf{e}_0$. Any deviation $d\mathbf{E}^3 = (d\mathbf{R}, d\Theta, d\Phi)$ from $\mathbf{e}_0$ represents an emotion vector **e** which can be resolved into a combination of the basis vectors $\mathbf{e}_{Bi}$, $i = 1\ldots3$. If **e** is a normalized vector, it is a barycentric combination of basis emotion vectors. Consequently, a sphere of unit radius in $\mathbf{E}^3$ would span all the possible emotions that would lead to 'realistic' or below realm of expressions (see figure 2). All the examples shown in this paper, as well as an implementation, consider an emotion vector space of dimensionality 3.

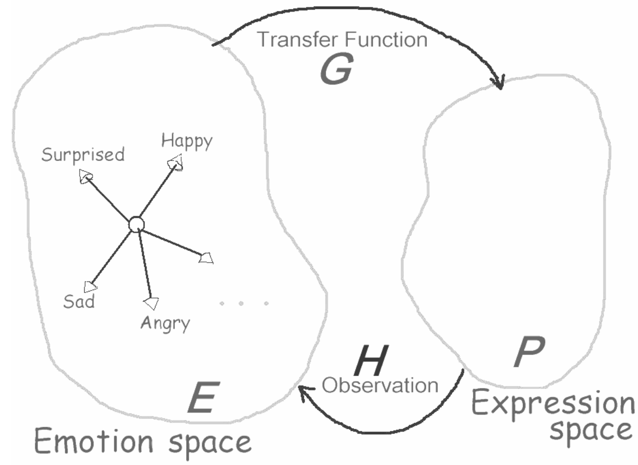


Figure 3: A conceptual view of our model. The infinite emotion space **E** spans unique emotion vectors. We start with a set of finite 'basis emotion vectors' $\mathbf{e}_i$ (e.g., happy, angry, surprised, etc.). A combination of one or more of $\mathbf{e}_i$ is mapped to a set of expression vectors $\mathbf{p}_i$ using an emotion to expression transfer function **G**. Unlimited new emotion vectors can be created based on observations from the expression space using the expression to emotion space transformation **H**. Note that the figure does not claim to depict the orthogonality of the basis functions. It is just a conceptual view. Further, only the vectors labeled 'happy', 'angry' and 'surprised' comprise the basis vectors. The vector labeled 'sad' is a synthesized or 'derived' emotion vector.

Any emotion vector with an increasing magnitude of its L2 norm (greater than unity) would eventually cross the realms of 'expressive' and 'hyper-realistic' expressions when transferred to the expression space. This notion is similar to the one mentioned in a recent work on motion-capturing cartoons [4]. However, we try to model it towards expressionism in facial expressions as opposed to in motion styles.

4 THE EXPRESSION SPACE

In addition to **E**, we define an associated expression space **P** in three-dimensional Euclidean space $\mathbf{R}^3$. **P** spans n expression vectors $\mathbf{p}_i$, where $0 < i \leq n$ (n is the number of discrete vertices in the associated face model **M**). Each $\mathbf{p}_i$ in addition has an associated motion transfer function f_i. This transfer function controls how much and when does an expression vector p_i transform the vertex $\mathbf{v}_i$ during animation with reference to $\mathbf{v}_j$, $0 < j \leq n$; $i \neq j$. The role of f_i is described in detail in section 5.1.

4.1 Synthesis of Expression Vectors

Consider an emotion vector e_i in emotion space **E**. We define an emotion to expression space transfer function

G, which generates a one-to-many mapping for all $\mathbf{e}_i$ from **E** into **P** as follows:

$$\mathbf{G: E \rightarrow P} \equiv g(\mathbf{e}_i) = \{ \mathbf{p}_j \,|\, j \in \mathrm{I}^+;\ 0 < j \leq n \},$$

Where

$\mathbf{p}_j$ is the expression vector for $\mathbf{v}_j$ in **M**.

The expression vectors $\mathbf{p}_j$ can then be obtained by the reverse mapping **H** as follows:

$$\mathbf{H: P \rightarrow E} \equiv h(\mathbf{e}_i, j) = \mathbf{p}_j \ |\ j \in \mathrm{I}^+;\ 0 < j \leq n$$

5 THE OBJECT SPACE

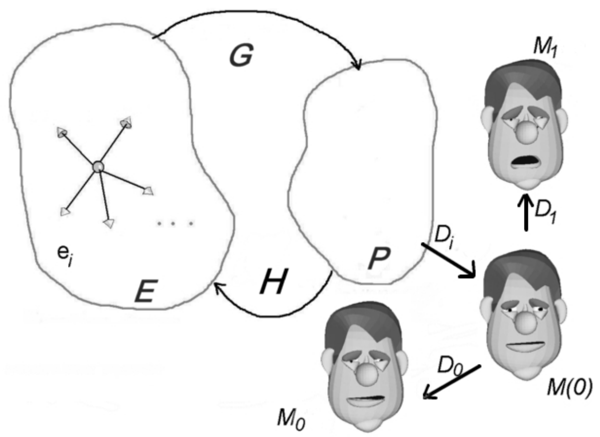


Figure 4: A complete emotion transfer cycle from **E** through **P** to the object space of **M**. **M**(0) is the face model with a neutral expression. Two emotion vectors $\mathbf{e}_0$ and $\mathbf{e}_1$ are transferred to the object space as $\mathbf{D}_0$ and $\mathbf{D}_1$, which transform **M**(0) to $\mathbf{M}_0$ and $\mathbf{M}_1$ respectively.

Once we have the expressions vectors corresponding to an emotion vector, we need a set of motion vectors to transform **M** into object space to yield the desired visual impression of a change of expressions.

5.1 Synthesis of Motion Vectors

We define $\mathbf{U} = \{\mathbf{u}_i \,|\, \mathbf{u}_i \in \mathbf{R}^3;\ i \in \mathrm{I}^+;\ 0 < i \leq n\}$ as a set of motion vectors that are used as affine transformation operators on **V** to map the synthesized expressions on **M**. This possibly empty set **U** is derived as follows:

$$\mathbf{U} = \{\mathbf{u}_j \,|\, 0 < j \leq n\} = \{f_j(\mathbf{p}_j) |\, 0 < j \leq n\}$$

where

f_j is the local motion transfer function for vertex $\mathbf{v}_j$ in **M**; and

$\mathbf{p}_j$ is the expression vector for $\mathbf{v}_j$.

Once we have this set of motion vectors, the model **M** can be transformed to yield the desired visual impression of expression change:

$$\mathbf{M'} \equiv \mathbf{V'} = \{\mathbf{v}_j + \mathbf{u}_j \ |\ 0 < j \leq n\}$$

However, for creating animations sequences, it is desirable to also have (k-1) intermediate model representations:

$$\mathbf{M}_0 \text{ -> } \mathbf{M}_1 \text{ -> } \ldots\ \mathbf{M}_i \ldots\text{-> } \mathbf{M}_{k-1} \text{ -> } \mathbf{M}_k$$

We can extend the single transformation expression without loss of generality to a parametric form:

$$\mathbf{U}(t) = \{\mathbf{u}_j(t) \,|\, 0 < j \leq n\} = \{f_j(t, \mathbf{p}_j) |\, 0 < j \leq n\}$$
$$\text{where } t \in \mathbf{R}$$

$$\mathbf{M}(t) \equiv \mathbf{V}(t) = \{\mathbf{v}_j + \mathbf{u}_j(t) \,|\, 0 < j \leq n\}$$
or
$$\mathbf{V}(t) = \mathbf{V}(0) + \mathbf{D}(t)$$
where
$$\mathbf{D}(t) = \{\mathbf{u}_j(t) \,|\, 0 < j \leq n\}$$

Notice that we have introduced an additional control parameter t over the degree of realism of the final expression. By not restricting t to a normalized linear scale, we can manipulate the visual impression of the mapped expression also in the expression space **P**. This allows us to smoothly blend between two emotions in **E** which manifest at the same degree of realism in the expression space. Also, the local motion transfer function f_i gives the flexibility of relative 'delay' in affine transformations of vertices over **V**. This gives an additional temporal control over the transition between expressions, providing additional flexibility to an animator.

5.2 Object Space Transformations

Now that we have formulated the emotion and expression space regimes, let us see how a basis or synthesized emotion vector **e** can be transferred to the object space of **M**. Consider again the Euclidean space that spans **V**, the set of discrete vertices that define **M**. To be able to map an expression originating as **e** in **E** onto **M,** our algorithm follows the following steps:

Step I. Induce an emotion in **E** as a combination (not necessarily barycentric) of $\mathbf{e}_i$:

$$\mathbf{e}^f = \Sigma\, w_i\, \mathbf{e}_i$$

(Note that if $\mathbf{e}_i \in \mathbf{E}_B\ \forall\ i$, and we divide $\mathbf{e}^f$ by $\Sigma\, w_i$, we have restricted the resultant emotion vector to stay inside the sphere of realism.)

Step II. Transfer the induced emotion vector $\mathbf{e}^f$ to expression space **P** to obtain a set of corresponding expression vectors $\mathbf{p}_j$:

$$g(\mathbf{e}_i) = \{ \mathbf{p}_j \,|\, j \in \mathrm{I}^+;\ 0 < j \leq n \}$$

Step III. Obtain **U**, the set of object space motion vectors:

$$\mathbf{u}_j = f_j(\mathbf{p}_j) \ \ \forall j$$

Step IV. Transform **V**:

$$\mathbf{V}' = \{\mathbf{v}_j + \mathbf{u}_j \mid 0 < j \leq n\}$$

However, when computing an animation sequence, steps III and IV are modified as

*Step III**. Obtain $\mathbf{U}(t)$, the set of object space motion vectors:

$$\mathbf{u}_j(t) = f_j(t, \mathbf{p}_j) \ \ \forall j$$

*Step IV**. Transform **V**:

$$\mathbf{V}(t) = \{\mathbf{v}_j + \mathbf{u}_j(t) \mid 0 < j \leq n;\ 0 \leq t\}$$

6 SYNTHESIS OF EMOTION VECTORS

Since emotion space is the origin of this expression synthesis framework, synthesis of meaningful emotion vectors is an important prerequisite to its success. For simplicity, we start with a finite number (four) of basis emotion vectors (see Table 1).

e vector	Emotion
$^{\#}\mathbf{e}_0$	Happiness
$\mathbf{e}_1$	Sadness
$^{\#}\mathbf{e}_2$	Anger
$^{\#}\mathbf{e}_3$	Surprise

Table 1. $\mathbf{E}_B$, the set of emotion vectors used for experiments, the results from which are shown in figures 1 and 5 (the color plate). #Denotes that $\mathbf{e}_i$ is a basis vector.

Conceptually, these emotion vectors can be created/acquired in one of the following three ways:

- Expression capture from images (abstract art, real photograph, caricature), video (real life [5, 7, 8, 9, 11, 19, 20], cartoon-animation) [*Acquisition*].
- Modeling by an artist [*Creation*].
- Automated synthesis from observation from the expression space **P** or within the emotion space [*Synthesis*].

Which one of these methods is used depends upon the application domain and the degree of realism desired therein. However, once the basis emotion vectors have been created/acquired, the combination method can be employed to populate $\mathbf{E}_S$, the set of synthesized vectors.

For the experimental domain of this work, a set of four basis emotion vectors were acquired from a set of expression vectors $\{\mathbf{p}_j\}$ using the reverse mapping **H** ($\mathbf{p}_j$ were computed from affine transformations on a face model manually mapped with a neutral and a desired expression.). Unfortunately, not much work has been pursued to propose a quantitative metric that measures the fidelity with which a vector in **E** represents an emotion. A recent work by Hendrix et al. [12] does address this issue, but their primary aim is to code and understand the relationship between primary expressions in emotion space. We foresee this as an important perceptual issue towards future research in expression synthesis.

7 IMPLEMENTATION AND RESULTS

The mathematical model described in the paper has been implemented on SGI™ workstations (O2, Octane and above) running Irix 6.5. OpenGL™ is employed as a rendering engine for hardware supported polygon rendering. The QT™ library for C/C++ language support was used to develop the graphical user interface. The sample face model used for experiments is composed of just 17 Bézier surface patches, each one described by a 5x5 control point array. It requires 12756 bytes of memory to store all the details necessary to create the images shown in figures 1 and 5 (the color plate).

8 CONCLUSIONS

We model an infinite emotion space **E** that is used for synthesis of a vast range of expressions. We also introduce a mapping between this emotion space **E,** and the expression space **P.** This model approximates the way facial expressions result from a living being's emotion space that the brain converts into muscle contractions. The linear independence property of basis emotion vectors in the emotion space allows for a continuous range of synthesized expressions. The model is a general concept and can be integrated with most of the existing mathematical models that work directly in expression space. It can be used to enhance the current techniques for face modeling in object space (manifold surfaces, muscle models, spring models, explicit analytical surfaces, etc.). Also, due to a generality of concept, a system based on this model can map a synthesized emotion vector to an arbitrary face model. However, we would like to mention that this method has been experimented only with caricature face models, and the initial basis emotion vectors used in the pursuit have *not* been synthesized by a professional artist. We hope that this work would introduce a new way of using perception behavior-based models for expressive facial animation.

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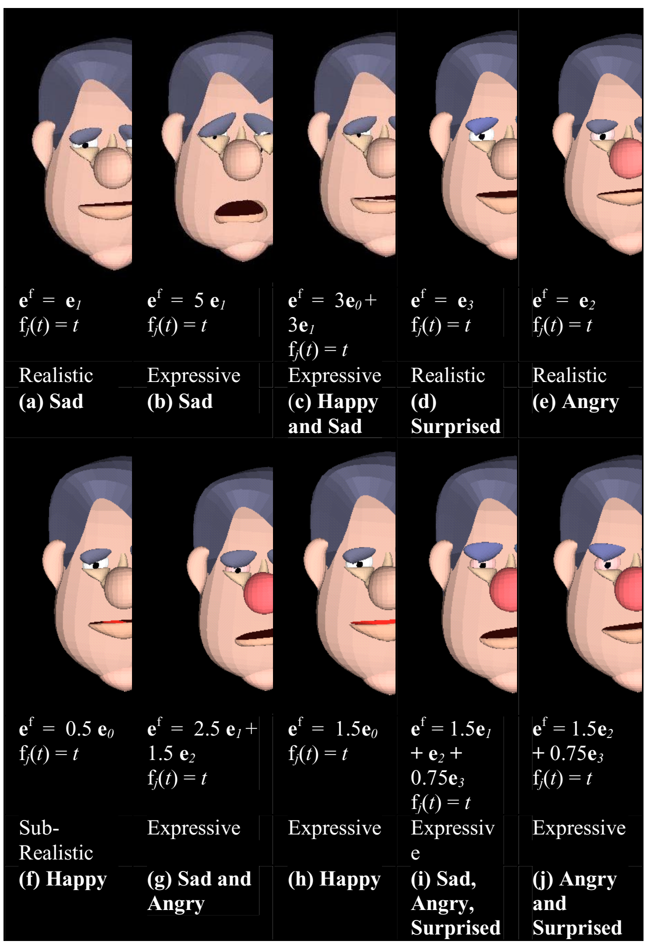
Color Plate



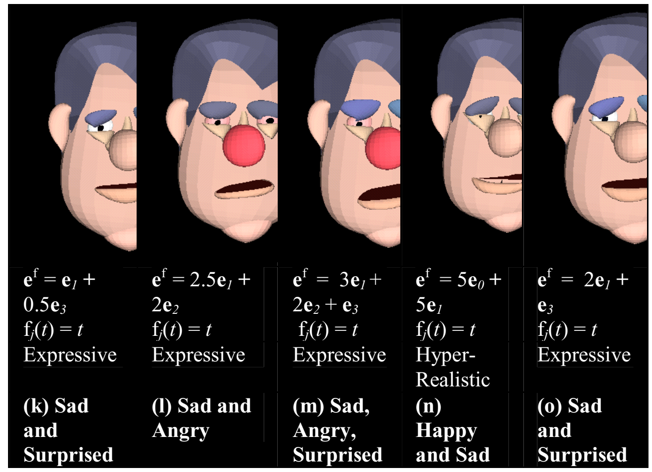


Figure 5: Some of the resulting images depicting expression synthesis over a cartoon face model. Notice how the expressions range from sub-real to realistic to really expressive. Images c, g, i, j, k, l, m, n, o show expressions resulting from induction of mixed emotions in the infinite emotion space E. Also note the change in the degree of realism as the synthesized emotion vector e^f spans out of the sphere of realism in E (images b, c, g, i, j, l, m, n, o).