A Bayesian explanation of the ‘Uncanny Valley’ effect and related psychological phenomena

Roger K. Moore

Department of Computer Science, University of Sheffield, Sheffield, S1 4DP, UK.

There are a number of psychological phenomena in which dramatic emotional responses are evoked by seemingly innocuous perceptual stimuli. A well known example is the ‘uncanny valley’ effect whereby a near-human-looking artifact can trigger feelings of eeriness and repulsion. Although such phenomena are reasonably well documented, there is no quantitative explanation for the findings and no mathematical model that is capable of predicting such behavior. Here I show (using a Bayesian model of categorical perception) that differential perceptual distortion arising from stimuli containing conflicting cues can give rise to a perceptual tension at category boundaries that could account for these phenomena. The model is not only the first quantitative explanation of the uncanny valley effect, but it may also provide a mathematical explanation for a range of social situations in which conflicting cues give rise to negative, fearful or even violent reactions.

The term ‘uncanny valley’ was coined by Masahiro Mori in 1970 to describe the observation that near-human artifacts can engender strong negative emotions in an observer (Fig. 1). For example, Mori noted that viewing a prosthetic hand can trigger feelings of eeriness and repulsion, whereas seeing a genuine human hand or a simple mechanical hand does not. He also proposed that the uncanny valley effect can be stronger when near-human artifacts are moving rather than still (as illustrated by the difference between the two curves illustrated in Fig. 1). Mori’s notion of the uncanny valley has entered into popular culture with lifelike artifacts (such as ‘Furby’ - the children’s toy), animated films (such as the 2004 feature ‘Polar Express’ starring Tom Hanks), and humanlike robots (such as ‘Geminoid F’) often being described by observers as ‘strange’ or ‘creepy’. In science and engineering the effect has become of increasing relevance to technical developments in the field of human-machine interaction as the fidelity of interface agents (either on-screen virtual agents or physical humanoid robots) reaches the point where feelings of repulsion could detract from the user experience and inhibit interaction.

Notwithstanding the widespread interest in the uncanny valley hypothesis, only a few studies have provided empirical evidence for its existence and, several have failed to find the effect at all. This lack of clear evidence one way or the other maybe due, in part, to some confusion over the precise nature of Mori’s dimension of ‘familiarity’. In fact, the term Mori used originally to describe his vertical axis - “shinwa-kan” - is a neologism in Japanese, and some authors have suggested that a more accurate translation would be ‘affinity’ rather than ‘familiarity’ – a proposal that fits well with the results reported here.

A number of accounts have been put forward, both for the effect itself and for why it is sometimes not apparent. For example, some studies have suggested a link between ‘eeriness’ and emotional responses associated with fear (particularly of death), and this may explain how a potentially universal effect can be obscured by systematic differences between subjects’ responses as a function of their personality type and emotional stability. Other studies have suggested that the effect might arise from a mismatch between different sensory cues, and recent results using fMRI scanning of the brain appear to support this hypothesis (as do the results reported here). Overall, the majority of explanations of the uncanny valley effect are based on empirical studies and, apart from a suggestion that it could be characterized using lateral inhibition, no mathematical model of the core result has been proposed hitherto.

It is hypothesized here that the uncanny valley effect is a particular manifestation of a more general psychological phenomenon in which perception is distorted by categorization. This so-called ‘perceptual magnet effect’, in which stimuli close to a category boundary are judged by observers to be more dissimilar than stimuli that are away from a category boundary, has recently been characterized mathematically by Feldman et al using
Feldman et al’s Bayesian model of categorical perception has been extended to account for differential perceptual distortion across multiple cues, and the enhanced model confirms that localized perceptual tension can indeed arise from differences in the distributions associated with such cues. In particular, the model reveals that cue conflicts can be manifest as variations in the means and/or variances of their associated distributions or, more interestingly, from unequal levels of uncertainty associated with observing the different perceptual cues. The latter is a particularly compelling result, since it indicates that perceptual tension can arise when the reliability of information derived from alternative cues to category membership is not balanced across different observation dimensions. For example, a humanoid robot might appear to be fully human from the cues provided by the overall facial features, but small anomalous movements in the eyes might be sufficient to increase the uncertainty associated with the category membership of that particular cue, thereby giving rise to perceptual tension (and feelings of discomfort) in the viewer.

The model shows that, in order to obtain Mori’s basic response curve (as illustrated in Fig. 1), it is necessary to posit a second category representing a ‘target’ perception (e.g. human) with the mean of its distribution at one end of the stimulus continuum. Then, in order for categorical perception (and the associated distortion of perceptual space) to occur, it is necessary to posit a second category representing a ‘background’ perception (e.g. non-human) whose distribution overlaps that of the target. The model also shows that in order to preserve the more or less monotonic property of the basic response curve (i.e. a rising function that depicts low familiarity at low human-likeness and high familiarity at high human-likeness), the distribution for the background needs to be broader than that for the target – an intuitively satisfactory outcome (see Fig. 2a). The model shows that, if the overlap between the target and background categories is reduced, a dip in ‘familiarity’ can be observed at the class boundary (see Fig. 2b). This dip reflects a degree of unfamiliarity (and hence unpredictability) associated with the stimuli around the category boundary. However, such a dip cannot go negative (since the curve represents probability), and does not in itself represent uncannyness. In fact, this intermediate result does indeed capture the concept of ‘familiarity’ but, crucially, not Mori’s notion of ‘affinity’.

Hence, the model reveals that there are two key variables that relate to Mori’s vertical ‘affinity’ axis: (i) the overall probability of occurrence of a particular stimulus, and (ii) any perceptual tension that might arise from conflicting perceptual cues. Not only does this approach lead to the successful prediction of the uncanny valley response curves, it also provides an explanation for the confusion over the nomenclature for Mori’s vertical axis (as described above). In the model presented here, ‘familiarity’ is defined mathematically as...
perceptual conflict and the sensitivity of an observer to any perceived 'uncannyness'. The depth of the dip is determined by the degree of differential distortion.

As an illustration of the output of the model, Fig. 3 shows how varying the differential uncertainty associated with cues along two perceptual dimensions (for the distributions illustrated in Fig. 2a) gives rise to different levels of localized perceptual tension (Fig. 3a) and hence to different curves for affinity/ eeriness (Fig. 3b). As can be seen, increasing the differential degree of uncertainty between the two cues leads to an increase in perceptual tension and a decrease in the affinity function near the category boundary, with the highest level of differential uncertainty leading to negative affinity. Clearly, the shapes of these curves are remarkably similar to those illustrated in Fig. 1, and the affinity measure does indeed appear to correspond to the notion of uncannyness as originally proposed by Mori.

As mentioned above, the other key aspect of Mori’s original uncanny valley hypothesis was that a moving humanlike artifact could be perceived as being more uncanny than the corresponding still humanlike artifact. Such a difference may be modeled in a number of different ways, but perhaps the simplest method is to regard a moving artifact as providing clearer information about its category membership, i.e. the distributions associated with a moving target category would be sharper (i.e. have lower variance) than those for a still target category. The output of the model for such a situation is shown in Fig. 4. With all of the other parameters held constant, a decrease in the variance for the target category leads to higher values of affinity either side of the category boundary and a deeper negative-going dip, precisely as predicted by Mori.

Discussion

One of the core ideas presented here is that the perceptual tension arising from conflicting cues to category membership may be experienced by an observer as physical or emotional discomfort (e.g. ‘creepiness’) which, in turn, may induce the observer to take action in such a way as to reduce its effect. In other words, such perceptual tension could act as an internal control signal that drives an observer to select one of a number of possible behaviors: (i) withdraw from the offending article, (ii) attempt to remove it by attacking it, (iii) actively ignore one or more of the conflicting cues (i.e. turning a ‘blind eye’), or (iv) integrate the new information in such a way that the misalignment between category boundaries is reduced (a form of learning that would lead to habituation). Clearly, which of these behavioral strategies is adopted by an observer would depend not only on the characteristics of the stimulus, but also on the personality and drive of the observer.

Indeed, although Mori’s original hypothesis (and much of the subsequent research into the uncanny valley effect) has been concerned with the response of human subjects to near-human artifacts such as avatars and humanoid robots, the model derived here provides a more general mathematical explanation (not necessarily unique to human behavior) for a range of real-world situations in which conflicting perceptual cues give rise to negative, fearful or even violent reactions. Possible responses to ambiguous stimuli range from feelings of disgust on encountering food that is off, negative reactions to individuals who are in some way different from the norm (such as ‘coulrophobia’ – fear of clowns), aggrievement at acts of blatant deception, amusement at sensory illusions, or physical illness as a result of sensory conflict.
Such outcomes align well with contemporary theories of emotion such as ‘cognitive appraisal theory’ in which stimuli are evaluated with respect to a series of evaluation checks, and the model may also be of some relevance to social theories of group belonging such as social identity theory and self-categorization theory in which uncertainty associated with inter-group and intra-group categorizations can lead to discriminatory behavior. The model may also provide an explanation for the opposite effect, i.e. why reactions to stimuli that are away from category boundaries may be judged as especially attractive.

Methods

Following Feldman et al., the distortion arising from the perceptual magnet effect along a single dimension can be modeled by a ‘displacement function’

\[ D(S) = E[T|S] - S \]

(1)

where \( E[T|S] \) is the expected value of the perceptual target \( T \) given a physical stimulus \( S \). The expected values are derived from the posterior probability of membership of a given category

\[ E[T|S] = \sum p(c|S) \left( \frac{\mu_c + \gamma c}{\sigma_c^2 + \sigma_s^2} \right) \]

(2)

for each category \( c \), where \( \mu_c \) is a category mean, \( \sigma_c^2 \) is a category variance and \( \sigma_s^2 \) is a measure of the uncertainty associated with observing the signal. Using Bayes’ theorem, the posterior probability is given by

\[ p(c|S) = \frac{p(S|c)p(c)}{\sum p(S|c)p(c)} \]

(3)

which can be modeled using

\[ S ~ \mathcal{N} \left( \mu_c, \sigma_c^2 + \sigma_s^2 \right) \]

(4)

where \( N \) is the normal distribution.

The displacement function \( D(S) \) represents a measure of perceptual distortion towards/away from the different categories along the dimension specified by the stimulus \( S \). A non-zero value of \( D(S) \) indicates that the perceived position of a particular stimulus \( S \) is displaced with respect to its actual physical value; a positive value indicates a distortion in one direction along the stimulus axis, and a negative value indicates a distortion in the opposite direction along the stimulus axis. A \( D(S) \) value of zero indicates that no perceptual distortion is present. The derivative of \( E[T|S] \) with respect to \( S \) is the familiar ‘discrimination function’ – a measure of perceptual warping that corresponds to the enhanced sensitivity to stimuli differences which can be modeled using

\[ V[S] = E[D(S)^2] - (E[D(S)])^2 \]

(5)

This expression is essentially a measure of the variance between the distortions present in each individual dimension. Hence \( V[S] \) is an indication of the amount of perceptual ‘tension’ that would arise as a result of differential distortions between conflicting perceptual cues. If all perceptual cues are in agreement with respect to the shapes and positions of category boundaries, then \( V[S] \) would be zero for all \( S \). If, on the other hand, \( V[S] \) is non-zero, then it implies that a particular stimulus \( S \) is not fully coherent in its support for the different categories.

Given that \( V[S] \) increases with greater perceptual conflict, it is hypothesized that subtracting \( V[S] \) from \( p(S) \) would provide a parsimonious combination function. In particular

\[ F[S] = p(S) - kV[S] \]

(6)

where \( F[S] \) corresponds to the vertical ‘affinity’ axis in Moris’ original diagram (Fig. 1), and \( k \) is a weighting factor that reflects the sensitivity of an observer to any perceived perceptual conflict.

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**Additional information**

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