A Phase Space Approach to Minimax Entropy Learning and the Minutemax Approximations

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Abstract

There has been much recent work on measuring image statistics and on learning probability distributions on images. We observe that the mapping from images to statistics is many-to-one and show it can be quantified by a phase space factor. This phase space approach throws light on the Minimax Entropy technique for learning Gibbs distributions on images with potentials derived from image statistics and elucidates the ambiguities that are inherent to determining the potentials. In addition, it shows that if the phase factor can be approximated by an analytic distribution then the computation time for Minimax entropy learning can be vastly reduced. An illustration of this concept, using a Gaussian to approximate the phase factor, leads to a new algorithm called "Minutemax," which gives a good approximation to the results of Zhu and Mumford in just seconds of CPU time. The phase space approach also gives insight into the multi-scale potentials found by Zhu and Mumford and suggest that the forms of the potentials are influenced greatly by phase space considerations. Finally, we prove that probability distributions learned in feature space alone are equivalent to Minimax Entropy learning with a multinomial approximation of the phase factor.

1 Introduction

Bayesian probability theory gives a powerful framework for visual perception [3]. This approach, however, requires specifying prior probabilities and likelihood functions. Learning these probabilities is difficult because it requires estimating distributions on random variables of very high dimensions (for example, images with 200×200 pixels, or shape curves of length 400 pixels). An important recent advance is the Minimax Entropy Learning theory. This theory was developed by Zhu, Wu and Mumford [7],[8],, [9] and enables them to learn probability distributions for the intensity properties and shapes of natural stimuli and clutter. In addition, when applied to real world images it has an interesting link to the work on natural image statistics [2][6][4]. We wish to simplify Minimax and make the learning easier, faster and more transparent. Ideally we would also like to determine which filters are useful (i.e. perform filter pursuit) without going to the trouble of learning their corresponding probability distributions.

In this paper we present a phase space approach to Minimax Entropy learning. This approach is based on the observation that the mapping from images to statistics is many-to-one and can be quantified by a phase space factor. If this phase space factor can be approximated by an analytic function then we obtain approximate "Minutemax" algorithms which greatly speed up the learning process. In some versions of this approximation, the unknown parameters of the distribution to be learned are related linearly to the empirical statistics of the image data set, and may be solved for in seconds or less. Independent of this approximation, the Minutemax framework also illuminates an important combinatoric aspect of Minimax, namely the fact that many different images can give rise to same image statistics. This "phase space" factor explains the ambiguities inherent in learning the parameters of the unknown distribution, and motivates the approximation that reduces the problem to linear algebra.

2 An Overview of Minimax

We wish to learn a distribution $P(\mathbf{I})$ on images, where $\mathbf{I}$ denotes the set of pixel values $I(x,y)$ on a finite image lattice, and each value $I(x,y)$ is quantized to a finite set of intensity values. [1] We define a set of image statistics $\phi_1(\mathbf{I}), \phi_2(\mathbf{I}), \ldots, \phi_S(\mathbf{I})$, which we concatenate as a single vector function $\vec{\phi}(\mathbf{I})$. (The statistics in Minimax Learning are defined in the next subsection in terms of histograms of linear or non-linear filter responses across entire images, but the results in this section generalize to any statistics that are deterministic functions of the image.) If these statistics have empirical mean $\vec{d} \equiv < \vec{\phi}(\mathbf{I}) >$ on a dataset of images (we assume a large enough dataset for the law of large numbers to apply; see Zhu and Mumford for an analysis of the errors inherent in this assumption) then the maximum entropy distribution $P_M(\mathbf{I})$ with these empirical statistics is an exponential (Gibbs) distribution of the form

$$P_M(\mathbf{I}) = \frac{e^{\vec{\lambda} \cdot \vec{\phi}(\mathbf{I})}}{Z(\vec{\lambda})}, \tag{1}$$

where the potential $\vec{\lambda}$ is set so that $< \vec{\phi}(\mathbf{I}) >_M = \vec{d}$.

In summary, the goal of Minimax Learning is to to find an appropriate set of image statistics for the domain of interest (i.e. the pursuit of maximally informative filters) and to estimate $\vec{\lambda}$ given $\vec{d}$. Extensive computation is required to determine $\vec{\lambda}$; the phase space approach to Minimax Learning motivates approximations that make $\vec{\lambda}$ easy to estimate.

Minimax Entropy Learning may also be presented in terms of the geometry of probability distributions, pioneered by researchers such as Rao and Amari. This *information geometry* perspective, as well the topic of filter pursuit and its connection to the phase space approach, are covered in Coughlan and Yuille [1].

3 A Phase Space Perspective on Minimax

How does a theory like Minimax Entropy Learning relate to the idea of going directly to feature space of images and learning distributions on these feature responses? We observe that the mapping from images to statistics is many-to-one and show it can be quantified by a phase space factor. This phase space approach throws light on the Minimax Entropy technique for learning Gibbs distributions on images with potentials derived from image statistics and elucidates the ambiguities that are inherent to determining the potentials. It demonstrates ways to estimate the potential $\vec{\lambda}$ approximately in a very quick manner (though, like many approximations, the approach does not always yield good results). In addition, it shows that if the phase factor can be approximated by an analytic distribution then the computation time for Minimax entropy learning can be vastly reduced. Finally, we prove that probability distributions learned in feature space alone are equivalent to Minimax Entropy learning with a multinomial approximation of the phase factor.

3.1 Image Histogram Statistics

First, we review the method of computing image histogram statistics. The statistics we consider (following [7],[8], and [9]) are defined as histograms of the responses of one or more filters applied

[1] In fact, this approach is general and applies to any patterns, not just images.

across an entire image. Consider a single filter f (linear or non-linear) with response $f_{\mathbf{x}}(\mathbf{I})$ centered at position $\mathbf{x}$ in the image. If the filter is linear, then this response may be defined in terms of convolution with a kernel k, i.e. $f_{\mathbf{x}}(\mathbf{I}) = (k \star I)(\mathbf{x})$. Without loss of generality, we will consider all filters as having quantized integer responses from 1 through f_{max}.

For notational convenience we transform the filter response $f_{\mathbf{x}}(\mathbf{I})$ to a binary representation $\vec{b}_{\mathbf{x}}(\mathbf{I})$, defined as a column vector with f_{max} components: $\vec{b}_{\mathbf{x},z}(\mathbf{I}) = \delta_{z,f_{\mathbf{x}}(\mathbf{I})}$, where index z ranges from 1 through f_{max}. This vector is composed of all zeros except for the entry corresponding to the filter response, which is set to one. The image statistics vector is then defined as the average of the $\vec{b}_{\mathbf{x}}(\mathbf{I})$'s over all N pixels:

$$\vec{\phi}(\mathbf{I}) = \frac{1}{N} \sum_{\mathbf{x}} \vec{b}_{\mathbf{x}}(\mathbf{I}).$$

The entries in $\vec{\phi}(\mathbf{I})$ then sum to 1. Note that the empirical mean of the statistics, $\vec{d}$, whose entries also sum to 1, can be regarded as a probability distribution specifying the empirical frequency of each possible filter response.

We can generalize to the case of multiple filters $f^{(1)}, f^{(2)}, \ldots, f^{(M)}$ with binary representations $\vec{b}^{(1)}_{\mathbf{x}}(\mathbf{I}), \vec{b}^{(2)}_{\mathbf{x}}(\mathbf{I}), \ldots, \vec{b}^{(m)}_{\mathbf{x}}(\mathbf{I})$. The m histograms $\vec{\phi}^{(1)}(\mathbf{I}), \vec{\phi}^{(2)}(\mathbf{I}), \ldots, \vec{\phi}^{(m)}(\mathbf{I})$, defined as $\vec{\phi}^{(i)}(\mathbf{I}) = \frac{1}{N_i} \sum_{\mathbf{x}} \vec{b}^{(i)}_{\mathbf{x}}(\mathbf{I})$, are concatenated into a single vector $\vec{\phi}(\mathbf{I})$. (Different filters may be defined at different scales of the image lattice, in which case a filter response may only be defined on a decimated version of the original lattice. For example, $N_i = N/4$ for a filter $f^{(i)}$ one level of coarseness above the original lattice.) In general we have $\sum_{i=1}^{S} \phi_i(\mathbf{I}) = m$, where $S = \sum_{i=1}^{m} f^{(i)}_{max}$. Again we note that $\vec{d}$, whose entries in this case sum to m, can be regarded as a set of m probability distributions, each specifying the empirical frequency of filter responses for one filter.

3.2 The Phase Factor

The original Minimax distribution $P_M(\mathbf{I})$ induces a distribution $P_M(\vec{\phi})$ on the statistics themselves, without reference to a particular image:

$$P_M(\vec{\phi}_0) = \sum_{\mathbf{I}} \delta_{\vec{\phi}_0, \vec{\phi}(\mathbf{I})} P_M(\mathbf{I}) = g(\vec{\phi}_0) \frac{e^{\vec{\lambda} \cdot \vec{\phi}_0}}{Z(\vec{\lambda})} \tag{2}$$

where $g(\vec{\phi})$ is a combinatoric *phase space factor*, with a corresponding *normalized* combinatoric distribution $\hat{g}(\vec{\phi})$, defined by:

$$g(\vec{\phi}_0) = \sum_{\mathbf{I}} \delta_{\vec{\phi}_0, \vec{\phi}(\mathbf{I})} \quad \hat{g}(\vec{\phi}) = g(\vec{\phi})/Q^N, \tag{3}$$

where the phase space factor $g(\vec{\phi})$ counts the number of images $\mathbf{I}$ having statistics $\vec{\phi}$, N is the number of pixels and Q is the number of pixel intensity levels, i.e. Q^N is the total number of possible images $\mathbf{I}$. It should be emphasized that the phase factor depends only on the set of filters chosen and is independent of the true distribution $P(\mathbf{I})$. Thus the phase factor can be computed offline, independent of the image data set.

Later in this paper we will discuss two useful approximations to $g(\vec{\phi})$: a Gaussian approximation, which yields the swift approximation for learning, and a multinomial approximation, which establishes a connection between Minimax and standard feature learning.

3.3 The Non-Uniqueness of the Potential $\vec{\lambda}$

Clearly, $\vec{\lambda}$ may be shifted by an additive constant ($\lambda_i \rightarrow \lambda'_i = \lambda_i + k$ for all i), yielding a different normalization constant $Z(\vec{\lambda'})$ but preserving $P_M(\mathbf{I})$. In this section we show that other, non-trivial ambiguities in $\vec{\lambda}$ which preserve $P_M(\mathbf{I})$ can exist, stemming from the fact that some values of $\vec{\phi}$

are inconsistent with every possible image $\mathbf{I}$ and hence never arise (in *any* possible image dataset). These "intrinsic" ambiguities are inherent to Minimax and are independent of the true distribution $P(\mathbf{I})$. We will also discuss a second type of possible ambiguity which depends on the characteristics of the image dataset used for learning.

We can uncover the intrinsic ambiguities in $\vec{\lambda}$ by examining the covariance C of $\hat{g}(\vec{\phi})$, defined as $C = \sum_{\vec{\phi}} \hat{g}(\vec{\phi})(\vec{\phi} - \vec{c})(\vec{\phi} - \vec{c})^T$, where we define the mean $\vec{c} = \sum_{\vec{\phi}} \hat{g}(\vec{\phi})\vec{\phi}$. (See [1] for details on calculating the mean $\vec{c}$ and covariance C for any set of linear filters or non-linear filters that are scalar functions of linear filters.) The null space of C is at least one-dimensional, reflecting a constraint on the set of allowed values of $\vec{\phi}$ (i.e. all $\vec{\phi}$ for which $g(\vec{\phi}) \neq 0$): namely, the sum of all histogram responses $\sum_{i=1}^{S} \phi_i(\mathbf{I})$ is constant, meaning that $C\vec{e} = 0$, where $\vec{e}$ is the column vector containing all ones. Defining the set of all possible statistics values $\Phi = \{\vec{\phi} : g(\vec{\phi}) \neq 0\}$, the null space of C reflects degeneracy (i.e. flatness) in Φ. As we will show in the following theorem, $\vec{\lambda}$ is determined only up to a hyperplane whose dimension is the nullity of C.

Theorem 1 (Intrinsic Ambiguity in $\vec{\lambda}$). $C\vec{\mu} = 0$ if and only if $e^{(\vec{\lambda}+\vec{\mu})\cdot\vec{\phi}(\mathbf{I})}/Z(\vec{\lambda} + \vec{\mu})$ and $e^{\vec{\lambda}\cdot\vec{\phi}(\mathbf{I})}/Z(\vec{\lambda})$ are identical distributions on $\mathbf{I}$.

Proof. $C\vec{\mu} = 0$ *implies* $\vec{\mu}^T C\vec{\mu} = 0$*, so that* $\sum_{\vec{\phi}\in\Phi} \hat{g}(\vec{\phi})\vec{\mu}^T(\vec{\phi} - \vec{c})(\vec{\phi} - \vec{c})^T\vec{\mu} = 0$*. But we can re-express this as* $\sum_{\vec{\phi}\in\Phi} \hat{g}(\vec{\phi})[(\vec{\phi} - \vec{c})^T\vec{\mu}]^2 = 0$*, and since each term is non-negative this implies that* $[(\vec{\phi} - \vec{c})^T\vec{\mu}]^2 = 0$ *for all* $\vec{\phi} \in \Phi$*. This expression may be written as* $\vec{\phi} \cdot \vec{\mu} = \vec{c} \cdot \vec{\mu}$ *for all* $\vec{\phi} \in \Phi$*, from which the forward result follows directly.*

To prove the converse, note that $\vec{\mu} \cdot \vec{\phi}(\mathbf{I})$ *must be constant for all* $\mathbf{I}$*, implying that* $\vec{\phi}^T\vec{\mu} = constant$ *for all* $\vec{\phi} \in \Phi$*. But then* $C\vec{\mu} = \sum_{\vec{\phi}\in\Phi} \hat{g}(\vec{\phi})(\vec{\phi} - \vec{c})(\vec{\phi} - \vec{c})^T\vec{\mu} \propto \sum_{\vec{\phi}\in\Phi} \hat{g}(\vec{\phi})(\vec{\phi} - \vec{c}) = 0$.

In addition to this intrinsic ambiguity in $\vec{\lambda}$, it is also it is possible that different values of $\vec{\lambda}$ may yield distinct distributions which nevertheless have the same mean statistics $< \vec{\phi} >$ on the image dataset. (As shown in [1], there is a *convex set of distributions*, of which the true distribution $P(\mathbf{I})$ is a member, which share the same mean statistics $< \vec{\phi} >$.) This second kind of ambiguity stems from the fact that the mean statistics convey only a fraction of the information that is contained the true distribution $P(\mathbf{I})$. To resolve this second ambiguity it is necessary to extract more information from the image data set. The simplest way to achieve this is to use a larger (or more informative) set of filters to lower the entropy of $P_M(\mathbf{I})$ (this topic is discussed in more detail [1]).

Alternatively, one can extend Minimax to include second-order statistics, i.e. the covariance of $\vec{\phi}$ in addition to its mean $\vec{d}$. Note that the covariance of $\vec{\phi}$ is well-defined in the standard Minimax distribution; it is quite possible that the *empirical* covariance may be significantly lower in certain dimensions than that predicted by standard Minimax. In other words, while Minimax might assume a large variation along these dimensions, a low empirical covariance would mean that second-order Minimax would restrict these variations. This added information would not only lower the entropy of $P_M(\mathbf{I})$ but would also produce long-range coupling between pixels that are far apart on the lattice. This is an important topic for future research.

4 The Minutemax Approximations

We now illustrate the phase space approach by showing that suitable approximations of the phase space factor $g(\vec{\phi})$ make it easy to estimate the potential $\vec{\lambda}$ given the empirical mean $\vec{d}$. The resulting fast approximations to Minimax Learning are called "Minutemax" algorithms.

4.1 The Gaussian Approximation of $g(\vec{\phi})$

If the phase space factor $g(\vec{\phi})$ may be approximated as a multi-variate Gaussian (see [1] for a justification of this approximation) then the probability distribution $P_M(\vec{\phi}) = g(\vec{\phi})\frac{e^{\vec{\lambda}\cdot\vec{\phi}}}{Z(\vec{\lambda})}$ reduces to another multi-variate Gaussian. As we will see, this result greatly simplifies the problem of estimating the potential $\vec{\lambda}$.

Recall that the mean and covariance of $\hat{g}(\vec{\phi})$ are denoted by $\vec{c}$ and C, respectively (see [1] for details on calculating these quantities). The null space of C has dimension n and is spanned by vectors $\vec{u}^{(1)}, \vec{u}^{(2)} \ldots \vec{u}^{(n)}$. As discussed in Theorem 1, for all *feasible* values of $\vec{\phi}$ and all $\vec{\mu}$ in the null space, $\vec{\mu} \cdot \vec{\phi}$ is a constant k. Thus we have that

$$g_{gauss}(\vec{\phi}) \propto \{\prod_{i=1}^{n} \delta_{\vec{\phi}\cdot\vec{u}_i,k}\} e^{-\frac{1}{2}(\vec{\phi}_r - \vec{c}_r)^T C_r^{-1} (\vec{\phi}_r - \vec{c}_r)}, \tag{4}$$

where the subscript r denotes projection onto the rank of C. Thus $P_{gauss}(\vec{\phi}) \propto g_{gauss}(\vec{\phi}) e^{\vec{\lambda}\cdot\vec{\phi}} \propto \{\prod_{i=1}^{n} \delta_{\vec{\phi}\cdot\vec{u}_i,k}\} e^{-\frac{1}{2}(\vec{\phi}_r - \vec{c}_r)^T C_r^{-1} (\vec{\phi}_r - \vec{c}_r) + \vec{\lambda}\cdot\vec{\phi}}$. Completing the square in the exponent yields

$$P_{gauss}(\vec{\phi}) \propto \{\prod_{i=1}^{n} \delta_{\vec{\phi}\cdot\vec{u}_i,k}\} e^{-\frac{1}{2}(\vec{\phi}_r - \vec{\psi}_r)^T C^{-1} (\vec{\phi}_r - \vec{\psi}_r)} \tag{5}$$

where $\vec{\psi}_r$ is the projection of any $\vec{\psi}$ that satisfies $\vec{\psi} = \vec{c} + C\vec{\lambda}$. Since $P_{gauss}(\vec{\phi})$ is a Gaussian we have $< \vec{\phi} >_{gauss} = \vec{\psi} = \vec{d}$, and so we can write a linear equation relating $\vec{\lambda}$ and $\vec{d}$:

$$\vec{d} = \vec{c} + C\vec{\lambda}. \tag{6}$$

It can be shown (Zhu – private communication) that this is equivalent to one step of Newton-Raphson for minimization of an appropriate cost function. This will fail to be a good approximation is the cost function is highly non-quadratic. As explained in [1], the Gaussian approximation is also equivalent to a second-order perturbation expansion of the partition function $Z(\vec{\lambda})$; higher-order corrections can be made by computing higher-order moments of $g(\vec{\phi})$.

4.2 Experimental Results

We tested the Gaussian Minutemax procedure on two sets of filters: a single (fine scale) image gradient filter $\partial I/\partial x$, and a set of multi-scale image gradient filters defined at three scales, similar to those used by Zhu and Mumford [9]. In both sets, the fine scale gradient filter is linear with kernel $(1, -1)$, representing a discretization of $\partial/\partial x$. In the second set, the medium scale filter kernel is $(U_2, -U_2)/4$ and the coarse scale kernel is $(U_4, -U_4)/16$, where U_n denotes the $n \times n$ matrix of all ones. The responses of the medium and coarse filters were rounded (i.e. quantized) to the nearest integer, thus adding a non-linearity to these filters. Finally, $\vec{d}$ was measured on a data set of over 100 natural images; the fine scale components of $\vec{d}$ are shown in the first panel of Figure (1).

A $\vec{\lambda}$ that solves $\vec{d} = \vec{c} + C\vec{\lambda}$ is shown in the second panel of Figure (1) for the first filter, and in the three panels of Figure (2) for the multi-scale filter set. (The solution to $\vec{d} = \vec{c} + C\vec{\lambda}$ was obtained by a fast gradient descent technique described in [1] to find a $\vec{\lambda}$ with minimum norm.) The form of $\vec{\lambda}$ is qualitatively similar to that obtained by Zhu (bearing in mind that Zhu disregarded any filter responses with magnitude above $Q/2$, i.e. his filter response range is half of ours). In addition, the eigenvectors of C with small eigenvalues are large away from the origin, so one should not trust the values of the potentials there (obtained by *any* algorithm.

Zhu and Mumford [9] report interactions between filters applied at different scales. This is because the resulting potentials appear different than the potential at the fine scale even though the histograms appear similar at all scales. We argue, however, that some of this "interaction" is due to *the different phase factors at different scales*. In other words the potentials would look different at different scales *even if the histograms were identical* because of differing phase factors.

4.3 The Multinomial Approximation of $g(\vec{\phi})$

Many learning theories simply make probability distributions on feature space. How do they differ from Minimax Entropy Learning which works on image space?

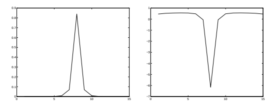

Figure 1: $\vec{d}$ on left, λ for first filter alone on right. (The λ is displayed with a minus sign for consistency with Zhu and Mumford's sign convention.)

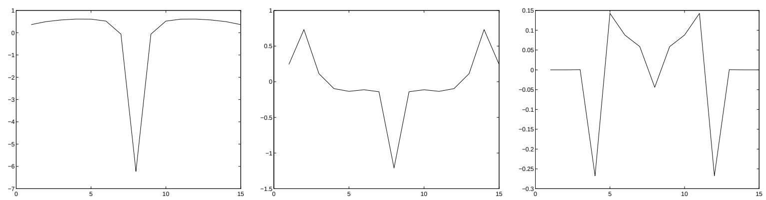

Figure 2: From left to right: the fine, medium and coarse components of λ.

By examining the phase factor we will show that the two approaches are not identical in general. The feature space learning ignores the coupling between the filters which arise due to how the statistics are obtained.

More precisely, the probability distribution obtained on feature space, P_F, is equivalent to the Minimax distribution P_M *if, and only if, the phase factor is multinomial.*

We begin the analysis by considering a single filter. As before we define the combinatoric mean $\vec{c} = \sum_{\vec{\phi}} \hat{g}(\vec{\phi})\vec{\phi}$. The multinomial approximation of $\hat{g}(\vec{\phi})$ is equivalent to assuming that the combinatoric frequencies of filter responses are *independent* from pixel to pixel. Since the combinatoric frequency of filter response $j \in \{1, 2, \ldots, f_{max}\}$ is c_j and there are $N\phi_j$ pixels with response j, we have:

$$\hat{g}_{mult}(\vec{\phi}) = \prod_{j=1}^{f_{max}} c_j^{N\phi_j} \frac{N!}{\prod_{j=1}^{f_{max}}(N\phi_j)!} \;\; and \;\; P_{mult}(\vec{\phi}) \propto \prod_{j=1}^{f_{max}} (c_j e^{\lambda_j/N})^{N\phi_j} \frac{N!}{\prod_{j=1}^{f_{max}}(N\phi_j)!}, \tag{7}$$

using $P_{mult}(\vec{\phi}) \propto g_{mult}(\vec{\phi}) e^{\vec{\lambda}\cdot\vec{\phi}}$. Therefore $P_{mult}(\vec{\phi})$ is also a multinomial. Shifting the λ_j's by an appropriate additive constant, we can make the constant of proportionality in the above equation equal to 1. In this case we have

$$< \phi_j >_{mult} = c_j e^{\lambda_j/N}, \;\; and \;\; \lambda_j = N \log(d_j/c_j) \tag{8}$$

by setting $< \phi_j >_{mult}$ to the empirical mean d_j.

Note that if any component d_j of the empirical mean is close to 0 then by equation 8 any small perturbations in d_j (e.g. from sampling error) will yield large changes in $\vec{\lambda}$, making the estimate of that component unstable.

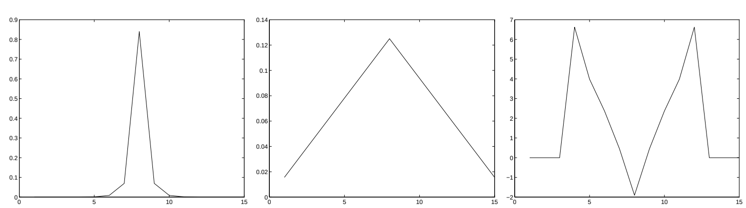

Figure 3: Left to right: $\vec{d}$, $\vec{c}$, and $\vec{\lambda}$ as given by multinomial approximation for the $\partial/\partial x$ filter at fine scale.

We can generalize the multinomial approximation of $g(\vec{\phi})$ to the multiple filter case merely by factoring $\hat{g}_{mult}(\vec{\phi})$ into separate multinomials, one for each filter. Of course, this approximation neglects all interactions among filters (and among pixels).

4.4 The Multinomial Approximation and Feature Learning

The connection between the multinomial approximation and feature learning is straightforward once we consider a distribution on the feature vector $\vec{f}$. This distribution (denoted P_F for "feature") is constructed assuming independent filter responses from pixel to pixel and whose statistics matches the empirical mean $\vec{d}$: $P_F(\vec{f}) = \prod_{i=1}^{N} d_{(f_i)}$, where f_i denotes the filter response at pixel i. Then it follows that $P_F(\vec{\phi})$ is a multinomial:

$$P_F(\vec{\phi}) = \prod_{j=1}^{f_{max}} d_j^{N\phi_j} \frac{N!}{\prod_{j=1}^{f_{max}} (N\phi_j)!} \tag{9}$$

Since $d_j = c_j e^{\lambda_j/N}$ by equation 8, we have that $P_F(\vec{\phi}) = P_{mult}(\vec{\phi})$.

5 Conclusion

The main point of this paper is to introduce the phase space factor to quantify the mapping between images and their feature statistics. This phase space approach can: (i) provide fast approximate "Minutemax" algorithms, (ii) clarify the relationship between probability distributions learnt in feature and image space, and (iii) to determine intrinsic ambiguities which may be resolved by second order statistics.

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