A Neural Network Approach to Photometric Stereo Inversion of Real-World Reflectance Maps for Extracting 3-D Shapes of Objects

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Abstract—In this paper, we present a neural network approach to the problem of photometric stereo inversion of the reflectance maps of real-world objects for the purpose of estimating the 3-D attitudes of the surface patches of objects. As in the photometric stereo approach, here also the observation that there is a one-to-one mapping between the $n$-tuples of the photometric stereo image intensities and the orientations of the surface normals is valid. A multilayered feedforward neural network with backpropagation training algorithm is used as dimensionality reducer to effectively encode this mapping by associating the two components of surface normals to the observed intensities from three photometric stereo images of the underlying surface patches. The training patterns are sampled from the images of a Gaussian sphere of average reflectance containing both diffuse and specular components. The neural network thus trained has been tested on images of real-world objects with different shapes and reflectance properties. Using the surface normals estimated by the neural network, 3-D shapes of the objects have been reconstructed to a good approximation.

I. INTRODUCTION

EXTRACTION of the 3-D shapes and orientations of objects from visual images has been a long standing quest of computer vision research. Among the various methods developed for this purpose using different cues, a class of computer vision methods called Shape From Shading (SFS) try to estimate the attitudes of the underlying surface patches from the image irradiance under given illumination conditions using a variational formulation, based on known reflectance models. These reflectance models give the implicit relation between the image irradiance and the orientation of the underlying surface. Since a number of different surface orientations can give rise to the same observed intensity, this problem turns out to be under-constrained. The SFS techniques proposed by Horn [1] and others formulate this problem as a non-linear optimization problem, stabilizing the main function to be optimized with additional constraints like surface smoothness, integrability in gradient space and occluding boundary conditions etc. [1], [2], [5], [7], [9]. The photometric stereo technique proposed by Woodham [2] provides a practical solution to this problem. In this technique and its variants, image intensities of a surface observed from one point but illuminated from different directions are used to mutually constrain one another to yield a closed form solution for the surface orientations [2]-[8].

The above techniques significantly depend on the explicit knowledge of the reflectance models of the object surfaces. Most of these techniques work successfully on the objects which conform to the well-understood diffuse-Lambertian reflectance model. Photometric stereo techniques proposed for the objects with both the diffuse and the specular reflectances either attempt to separate the two using multiple images and consider only the diffuse component for the estimation of the surface orientation or use extended light sources with spatially varying intensities, with complex irradiance equations [3], [4], [6]. The actual nature of the reflectance of most of the real-world surfaces is observed to be generally a hybrid of diffuse, specular and possibly other kinds of reflectances as well [8]. Thus the existing computer vision techniques are limited by the complexity and the paucity of analytical models that approximate the actual real-world phenomena. Moreover, the above techniques are highly susceptible to noise since they work at pixel level. Hence, there is a need for a noise tolerant, stable and generalized technique that can work on the real-world object surfaces without a model of their reflectance characteristics. In this pursuit a neural network based approach to estimate the 3-D attitudes of real-world object surfaces from photometric stereo images has been investigated in this work.

In the photometric stereo approach, the distribution of the $n$-tuples of intensities from $n$ photometric stereo images corresponding to all possible orientations of a visible surface is observed to form a 2-dimensional constraint surface, since the local surface orientation can have only two degrees of freedom. Further, since the observed intensity is a monotonic function of the surface orientation for any given reflectance map, this constraint surface is observed to be a topological map of the two components of the surface normals. Hence, we propose to address the problem of photometric stereo inversion as a dimensionality reduction problem using the multilayered feedforward neural network as a dimensionality reducer. In this approach, a neural network is required to be trained to abstract the inverse mapping between the observed intensities from three photometric stereo images and the two scalar components of the corresponding surface normals. This concept of the topological map and the proposed neural network approach are schematically shown in Fig. 1.

The multilayered feedforward neural network with steepest gradient descent method of learning, henceforth referred to
knowledge of any analytical relation between the two, its property to generalize on untrained patterns with graceful degradation and its noise tolerance properties [10]. While the most successful use of BPN has been as a classifier, in the present work it has been used as a dimensionality reducer by the virtue of its self-organizing property in encoding even non-linear constraint surfaces embedded in a higher dimensional space as demonstrated by Eric Saund [13]. In this role, the neural network is expected to counter what may aptly be called the curse of dimensionality and thereby remove the consequent effects of low cardinality training sample sets.

For the purposes of training the neural network, a Gaussian sphere is used as a calibration object, since a sphere is an ensemble of surface patches with all possible orientations. Assuming only an average hybrid reflectance of the surface, the photometric stereo images of the sphere are synthesized and the training exemplars are generated at each of the uniformly sampled locations in the image plane. In the standard BPN paradigm, the training exemplars are independent of each other and hence the neighbouring patterns from the input space do not necessarily produce coherent response from spatially contiguous output neurons. To achieve such spatial coherence, which is the essence of the topological map, a scheme of distributed encoding of the target patterns has been adapted in this work for learning the desired mapping. The basic approach and the first results are reported in [15]. The neural network thus trained is expected to generalize on real-world surfaces with variations in the reflectance properties. An important aspect of the proposed approach is that no assumed constraints like continuity constraint is imposed on the model; rather, the neural network is made to learn the natural constraints from the examples.

The paper is organized in the following sections. The theoretical background of the photometric stereo technique for general surfaces is discussed in Section II. In Section III, various aspects of the proposed neural network approach are presented. Implementation details and results are presented in Section IV, followed by conclusions in Section V.

II. THEORY

A. Photometric Stereo Inversion

Radiometry studies explain how the intensity image of a 3-D object depends on its shape, the reflectance properties of its material and the direction of the illumination. For a surface of uniform reflectance, when the light source as well as the viewer are sufficiently distant as depicted by imaging geometry in Fig. 2 and the inter-reflections between the object surface patches are absent, this dependence is expressed as an irradiance equation

\[ E(x, y) = R(i, n, r) \]  

(1)

where, \( E(x, y) \) is the irradiance at the observed point \( (x, y) \), \( R(i, n, r) \) is the so called Reflectance map, \( i \) is the unit vector along the direction of incident light, \( r \) is the unit vector along the direction of the reflection and \( n \) is the unit surface normal. \( R(i, n, r) \) is proportional to the radiance of the
light source and the reflectance of the surface characterized by its Bidirectional Reflectance Distribution Function (BRDF) which in turn is defined as the ratio of the irradiance of reflected light to the irradiance of incident light [1], [2].

The irradiance (1) in its full form [2] is a non-linear equation of the components of the surface normal \( n = [n_x, n_y, n_z] \) and provides only a partial constraint on the possible surface normals giving rise to the image irradiance \( E(x, y) \). Complete constraining is possible in the photometric stereo technique by the use of multiple images of the same surface, observed from the same view point, but illuminated from different directions. These images are characterized by a set of irradiance equations given by

\[
E_1(x, y) = R(i_1, n, r) \\
E_2(x, y) = R(i_2, n, r) \\
\vdots \\
E_k(x, y) = R(i_k, n, r) 
\]

(2)

In the conventional methods proposed by Woodham and others, these simultaneous equations are solved to obtain a closed form solution for the surface normal \( n \).

B. m-Lobed Reflectance Map

Solution of the photometric stereo equations needs an accurate knowledge of the characteristic BRDFs of the surfaces. Tagare et al. [8] have reviewed various BRDFs proposed in the literature to explain the different reflection phenomena and have formulated a unified model for the real-world reflectances. They observed that most solids are not perfectly regular; rather they exhibit varying reflectance properties due to the bulk and the surface inhomogeneities. Reflections from most of the engineering surfaces are found to be contained in three lobes [Fig. 3]. The forescatter lobe is spread around the specular direction, the normal lobe is spread around the mean surface normal and the backscatter lobe is spread around the incident direction. Integrating the product of the source irradiance and the BRDFs for different lobes, the simplified Reflectance map from physical considerations for most of the surfaces can be given as

\[
R(i, n, r) = \rho_{fs}\Phi(n_T^T n) + \rho_{norm}(i_T^T n) + \rho_{bsc} \tag{3}
\]

for \((i^T n) > 0\).

Here \( n_s \) is the unit vector along the specular direction, \( \Phi() \) is a monotonically increasing function of its argument given by the well known rendering models like those of Phong, Torrance-Sparrow etc. [6], \( \rho \)'s are constants called ‘albedos’ for the forescatter, the normal and the backscatter lobes respectively. Generalizing (3), an \( m \)-lobed reflectance map has been proposed [8] to accommodate any other possible reflection phenomena as well. It is given by

\[
R(i, n, r) = \sum_{j=1}^{m-1} \rho_j \Phi(p_j^T n) + b \tag{4}
\]

for \((p_j^T n) > 0\), where \( b > 0 \) is a constant.

It is clear from this model that any practical algorithm which takes into consideration the real-world reflectance phenomena has to estimate all the unknown reflectance parameters along with the surface normal and this complicates the solution methodology. Thus, the solution to the photometric stereo inversion problem of the real-world surfaces by analytical techniques is limited by the mathematical modeling of the reflectances and the instability of the same when applied to real images which are invariably noisy. In this context we observe that a neural network approach that overcomes the need to analytically model the real-world phenomena is more advantageous.

III. PROPOSED NEURAL NETWORK APPROACH

In this section we first present the basis for using the BPN as dimensionality reducer and then a scheme for training the BPN for the purposes of photometric stereo inversion on this basis.

A. Constraint Surface in Intensity Space

If three-light sources are used (i.e., \( k = 3 \)) the normalized photometric stereo equation given by (3) can be viewed as a mapping from the surface normal \([n_x, n_y, n_z]\) to \([E_1, E_2, E_3]\). The domain of the mapping is the manifold defined by
Fig. 4. (a) Light source positions for photometric stereo application and the distribution of photometric stereo intensities for surfaces having (b) only diffuse-Lambertian reflectance. (c) Hybrid reflectance with diffuse and specular components.

$n^Tn = 1$. In other words, since the local surface orientation has only two-degrees of freedom, the image irradiance as a monotonic function of the surface normal is constrained to be distributed across a 2-D surface in a 3-D photometric stereo intensity space. The manifold structures of the distribution of observed intensities when illuminated from three symmetrically located directions are shown in Fig. 4, both for a surface with only diffuse reflectance and for a surface with hybrid reflectance having both the diffuse and the specular components.

Since the variation of the surface normal with two-degrees of freedom is topologically preserved in the variation of photometric stereo intensities, the manifold constraint-surface is a topographic map of the underlying surface normals.
Formally the same can be observed as a parametric surface in \( n_x \) and \( n_y \), where \(-1.0 \leq n_x, n_y \leq 1.0\).

Hence, we may view the photometric stereo inversion as a dimensionality reduction problem, in which a mapping is established between the \( n \)-dimensional photometric stereo intensity vector \([E_1, E_2, \ldots, E_n]\) and the two components of the surface normal \( n_x \) and \( n_y \). Although three intensities are shown to be sufficient for the purpose as shown by Woodham and others, more may also be used.

**B. Supervised Self-Organizing Using BPN**

The motivation to explore neural models for dimensionality reduction comes from the topographical organization of the brain cells. Several of the brain maps e.g., auditory maps, visual maps, motor maps etc. are observed to be essentially sheets of neurons topologically mapping the corresponding multi-dimensional sensor fields. The spatial location of a cell or its cell groups on such a two-dimensional map corresponds to a particular domain of input signal patterns, thus topologically mapping the multi-dimensional information onto the two-dimensional map. In the artificial neural networks (ANN), such spatial coherence in the responses of the output neurons can be achieved through the correlated training of the spatially neighbouring cells using various lateral interactions. Amari [11] provides a comprehensive theory and mathematical analysis of the formation of the topological maps and the neural representation of information in such maps. While Kohonen’s self-organizing map (SOM) provides an unsupervised learning paradigm for evolving such maps from the physical data [12], an alternative BPN paradigm has been proposed by Eric Saund for such dimensionality reduction problems [13].

In the present work, since the correspondence between the input and the output dimensions of the constraint surface to be encoded is known, we adopt the supervised learning paradigm of BPN. The dimensionality reduction is achieved by encoding the mapping between the three observed photometric stereo intensities and the corresponding two components of the surface normals. In this approach, which may be called supervised self-organizing, the output response of the BPN is topographically mapped on to the spatially ordered output neurons. Fig. 5 schematically shows the spatial organization of the two sets of the output neurons encoding the scalars \( n_x \) and \( n_y \) corresponding to the input intensity vector \([E_1, E_2, E_3]\).

In the BPN paradigm, since each of the training exemplars are essentially independent of other exemplars, spatially neighboring patterns from the input space do not necessarily activate spatially contiguous output neurons, whereas spatial coherence in the response of the network is necessary to efficiently encode the topological mapping between the input and the output patterns. Such spatial coherence can be induced during training by the distributed encoding of the patterns. The distributed encoding of the patterns onto spatially contiguous set of neurons enforces neighbouring neurons to adapt to a specific spatial response with varying degrees, thereby facilitating the topographic ordering of the mapping being encoded. The finite set of neurons representing a scalar component of a pattern may be termed as a scalar set. The pattern of activity of a scalar set to represent a scalar \( x \) is determined by placing a unimodal smearing function on the grid of neurons with modal value \( x \) and sampling the same at fixed points along a normalized interval at which the neurons are positioned. In the present work we choose the Gaussian function \( G(x, \sigma) \) for this purpose over the interval \([-1.0 \text{ to } 1.0\) which is the range of the scalars to be encoded, namely, the two components of the surface normals. Each component is represented over a set of 21 output neurons in the current work. A sample input intensity vector and the corresponding surface normals encoded as an output vector are shown in Fig. 6(a) and (b), respectively.
The form of the smearing function chosen facilitates a strategic control over the spread of the pattern of activity through the parameter $\sigma$. This provides a means of skirting the local minima by smoothing the error surface during training by initially encoding the target patterns with a large spread of activities and gradually localising the spread as the training proceeds by reducing $\sigma$. A large spread of distributed activation during the initial stages of training ensures that any target response will not be too different from that of its neighbouring patterns and hence the changes in the mean squared error will be minimal. This essentially removes the high frequency undulations in the error surface which are primarily responsible for the local minima. This strategy, in a fashion somewhat similar to that of Kohonen's self-organizing maps, enforces a global order in the connection weights as well. As the training proceeds, restoring the error surface by gradually reducing the spread of target activity improves the spatial resolution of the mapping without disturbing the global order. In what may be called fine-tuning of output neurons to target responses, the spread of activity can be reduced according to a linear schedule given by

$$\sigma(t) = \left(1 - \frac{t}{t_{\text{max}}\right)\sigma_{\text{max}}$$  \hspace{1cm} (5)$$

where, $t = \text{training time or iteration number}$. Alternately, a step change can be made after a fixed number of iterations and in that case $t$ will represent the step number.

Further, while testing the trained network any pattern of activity $a$ over a scalar set of $n$ output neurons will have to be decoded into the scalar component $x$ in the interval $(-1.0,1.0)$. This can be done by determining $x$ that minimizes the squared difference

$$E = \sum_{i=1}^{n} (G(x, \sigma_{i}) - a_{i})^2$$  \hspace{1cm} (6)$$

where $G$ is the smearing function whose $\sigma$-value has been fixed during training. A closed form solution for $x$ can be obtained by setting

$$\frac{dE}{dx} = 0.$$  \hspace{1cm} (7)$$

Alternatively, the decoding can be performed by directly estimating the location of the mode of the pattern of activity over the scalar set. As the mode could lie in between the positions of two consecutive neurons with highest activities, an interpolation method could be used to estimate the correct positions. In this work, for reasons of efficiency, we used a look-up table to estimate the interpolated modal value.
C. Gaussian Sphere as a Calibration Object

We propose to use a Gaussian sphere with $m$-lobed reflectance as a calibration object as suggested by Horn [1], since a sphere is an ensemble of surface patches with all possible orientations. Photometric stereo images of the sphere illuminated by three point light sources symmetrically located as shown in Fig. 4 are taken. The training set consists of the observed intensities from the three images as input and the corresponding surface normals as target patterns at the locations sampled from all over the visible surface of the sphere.

To induce noise tolerance in the model, observed intensities from a $5 \times 5$ neighbourhood of the sampled locations are taken as input pattern. The target output pattern consists of the two scalar components of the surface normal, corresponding to each input patch, which can easily be determined from the known geometry of the sphere.

Once trained, the network is expected to generalize on any surface with unknown $m$-lobed reflectance map and output the two estimated components of the surface normal, when given the observed intensities from the three photometric stereo images taken under the same imaging geometry as that of the trained patterns.

IV. IMPLEMENTATION DETAILS AND RESULTS

The above neural network approach has been implemented for reflectance maps in the form given by (3), which approximates many real-world surfaces. For training, synthetic photometric stereo images of the Gaussian sphere were generated on a HP9000/350-SRX workstation computer. The backpropagation neural network was simulated on a PC386, with ANZA-Plus neuro-computing co-processor. The details of the implementation and the results are given in the following subsections.

A. Training the Neural Network

The imaging geometry used and the distribution of intensities in the photometric stereo images of the calibration object...
are as shown in Fig. 4. The input to the neural network consists of a set of observed intensities from a 5 x 5 neighbourhood of the point of interest from each of the three photometric stereo images of the Gaussian sphere, resulting into a total of 75 processing elements (PE) at the input layer. The target pattern, comprising the components of the surface normals \( n_x \) and \( n_y \) are generated as explained earlier by sampling a Gaussian smearing function \( G(x, \sigma) \) over a set of 21 PEs for each component, making the total number of PEs in the output layer 42. The hidden architecture was determined experimentally by changing the same, until the satisfactory results were obtained.

The locations of the sampled training patches on the image plane are shown in Fig. 7. To accommodate the steeper variation in the observed intensities due to specularity, more training patches were sampled from the specular regions. A sample target pattern with a decreasing spread is shown in Fig. 8(a). The mean squared error plots corresponding to training with the two extreme spreads of the target patterns are shown in Fig. 8(b). The training curves for the patterns with intermediate spreads are observed to lie in between these two extremities. Further it can be observed from the plots that the network converges faster when the spread of the target patterns was larger and was not able to converge to the required error level when the target pattern activity was localized. This observation clearly demonstrates the strategic control provided by the smearing function in smoothening the error surface. After the initial convergence with the error surface smoothened in this way, the network was fine-tuned by gradually reducing the spread of target pattern activity in steps as per the schedule given by (5), with \( \sigma_{\text{max}} = 3.5 \) and \( t_{\text{max}} = 7 \). The training was continued until the mean squared error in the surface normals estimated all over the surface of the calibration object was reduced to a satisfactory level.

The final architecture arrived at after experimentation, was a network of two hidden layers with 120 and 115 PEs in the first and the second hidden layers respectively, when it was trained using a calibration object having a hybrid reflectance with both diffuse and specular components. For a calibration object having only the diffuse reflectance, the network needed only 70 and 65 PEs in the first and the second layers respectively, for successful training. The larger hidden architecture needed in the case of the hybrid reflectance can be substantiated by the presence of large curvatures in the encoded manifold owing to the non-linear components in this model (Fig. 4).
Fig. 13. (g) One of the three photometric stereo images of an aluminum cylinder; (h) Surface normals estimated by the trained neural network from the images of the aluminum cylinder. (i) Perspective view of the 3-D surface of the aluminum cylinder reconstructed from the estimated surface normals.

of a smearing function for distributed encoding of scalars and for inducing spatial coherence in efficiently learning the topographic mapping between $n$-tuples of intensity and scalar components of surface normals has been demonstrated.

The proposed approach has been successfully used for applying the photometric stereo method on the real-world objects with reflectance characteristics varying from pure diffuse to highly specular reflectances. The 3-D shapes reconstructed from the surface normals estimated by the neural network are found to be a good approximation of the actual shapes. The model is shown to be robust against the noise and the deviation in the reflectance properties of the test surfaces from that of the calibration object.

It may be emphasized that the reliable estimation of surface attitudes has been possible with the present neural network approach without explicit analytical models for reflectance properties of different surfaces. Apart from the generalizing ability of the neural network, the superior performance of the neural network as compared to that of the analytical model is observed to be the consequence of the distributed representation of the topographic mapping which was achieved through the distributed encoding of the target scalar patterns using the smearing function. Also the improved robustness against noise can be attributed to the use of neighborhood information from the input images rather than pixel level information as in the case of the analytical model.

As far as the complexity of the proposed neural network model is concerned, it is the same as that of the standard BPN with steepest-gradient descent method of learning. However, it is observed that the size of the hidden architecture increases with the increase in the number of lobes present in the reflectance model being abstracted. This fact only complements the well-known properties of the multilayered feed-forward networks that the number of hidden elements increases with increasing non-linearity in the mapping and that given a sufficient number of hidden sigmoidal elements, such networks
real-world surfaces. For this purpose, real objects of various shapes and made of materials having different reflectance characteristics were selected. One of the objects was a foundry pattern made of wood with only diffuse reflectivity, another one was a dome shaped object with a through-hole, made of plastic having both diffuse and specular reflectances and yet another object was a cylinder made of aluminum with highly specular reflectance. The objects were illuminated by incandescent light sources and the photometric stereo images were acquired through a CCD camera. The trained neural network was tested on the images thus acquired. Fig. 13 shows one of the three photometric stereo images, surface normals estimated by the neural network and the 3-D shape reconstructed from the surface normals thus estimated. The results show that the reconstructed shapes are very close to the actual shapes and amply demonstrate the robustness of the neural network against variations in reflectance properties.

V. CONCLUSIONS

In this paper, a neural network based approach has been proposed to estimate the orientation of 3-D surface patches from photometric stereo images of the objects with m-lobed reflectance characteristics. An important aspect of the proposed approach is that no constraints like continuity constraints are imposed on the model and neural network is made to learn the natural constraints from examples. In the proposition, the photometric stereo inversion is analyzed as a dimensionality reduction problem from 3-space of photometric stereo intensities to that of two scalar components of the corresponding surface normals. For this purpose, the use
of a smearing function for distributed encoding of scalars and for inducing spatial coherence in efficiently learning the topographic mapping between n-tuples of intensity and scalar components of surface normals has been demonstrated.

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can realize any continuous input-output mapping to a given accuracy. The latter property augments our contention that the proposed approach can be used to learn the inverse mapping of any $m$-lobed reflectance map. Further, since the estimation of surface normal relies only on the local neighbourhood information, the trained neural network can be copied in space to estimate the surface normals simultaneously from all over the visible surface. This feature, along with the inherent parallelism of the neural network itself, makes the proposed model viable for parallel implementation as well.

REFERENCES


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