A s ... rt ... s ... t o ort ... n r ... ton o ... r ... n ... on ov rpos ... n pr ss ... on

... ron D uv ... v n ... B ... r ... on E ... n
A Jon ... n H ow ... H ... r Bu ton

C ...

J nu r ...

I ...

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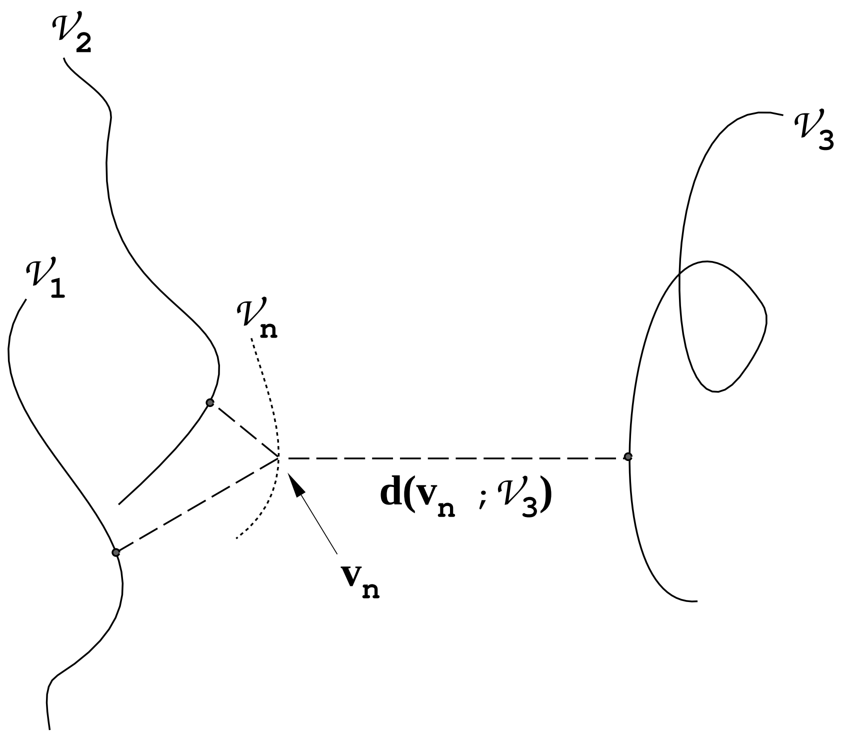
C o n ... v ... n ...
... s ... r ... p rs

A similarity-based method for the generalization of face recognition over pose and


$\mathcal{V}_2$
$\mathcal{V}_3$
$\mathcal{V}_1$
$\mathcal{V}_n$
$\mathbf{d}(\mathbf{v}_n\ ;\mathcal{V}_3)$
$\mathbf{v}_n$

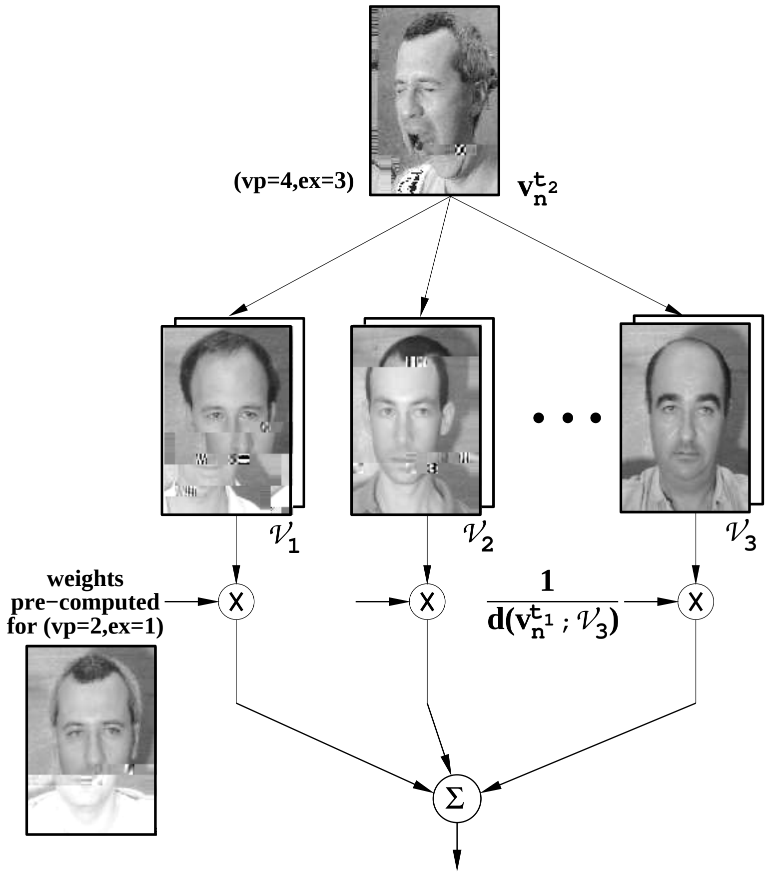


Figure 2: A mechanism for estimating the viewsu12l4072.60e2Tf100-15(thehanism)]a9lA

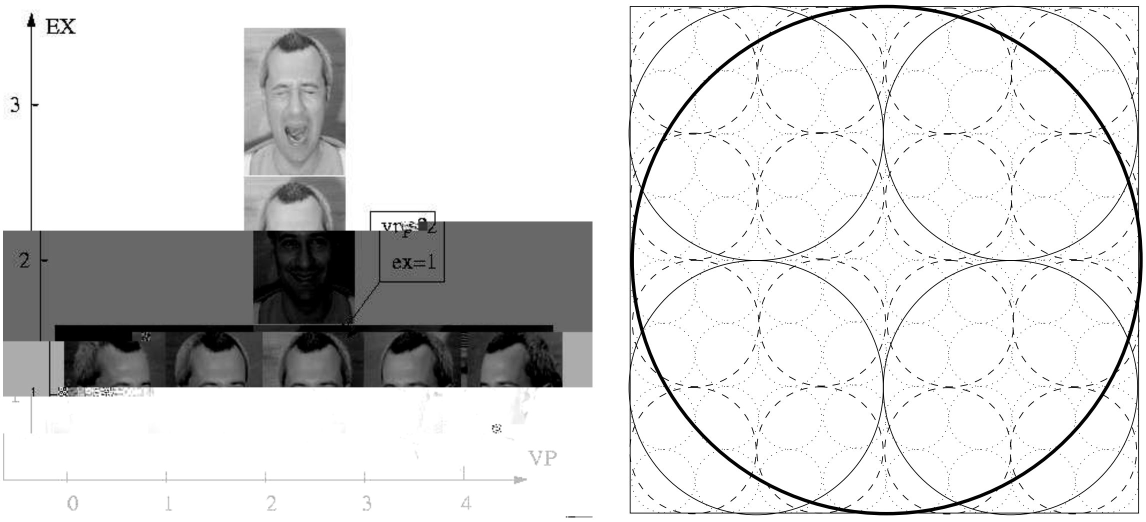


Figure 3: *Left:* the dimensions of variation in the fa1(386)Tj63737.llustr(3[Wcn602.21i95c4[2f[(TTd5c8.5able131287164y695c6

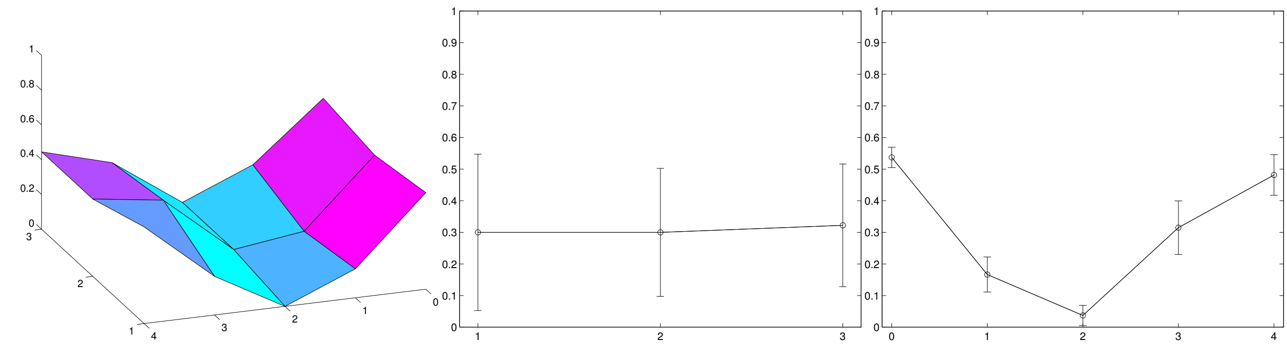


Figure 4: *Left:* a surface plot of the error rate vs. VP and EX (the numbers are listed in Table 1). *Middle:* error rate vs. VP, averaged over the three different values of EX. *Right:* error rate vs. EX, averaged over the five different values of VP. The mean error rate over the five viewing positions (spanning a range of $\pm 34°$ in orientation), and the three expressions was 0.3074. The error bars correspond to ± 1 standard error of the mean computed over the 18 test faces.

perience with similar objects (i.e., other faces seen in a variety of conditions) serves to guide the system in its treatment of the stimulus. Since the introduction of this concept of so-called class-based processing [10, 14, 2, 11], several applications to face recognition and related problems have been published [17, 4, 3]. Typically, these methods rely on the establishment of a dense correspondence field, before any recognition or generalization is attempted. Approaches that gave up this constraint showed a certain promise [9], but could not compete, performance-wise, either with the human subjects, or with the more sophisticated correspondence-based methods.

In the present work, the employment of a front end containing Gabor filters at multiple scales and orientations [8] served to reduce the need for detailed pixel-by-pixel correspondence, and allowed the viewspace interpolation method [5] to be utilized to its full potential. We conjecture that a further improvement in the front-end measurement stage, combined with a more advanced approach to interpolation (which is currently done by inverse-distance weighting), will close most of the remaining gap between the system's 3-way discrimination error (8%) and the error exhibited by human subjects (3%).

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