A s rt s t o ort n r t on 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

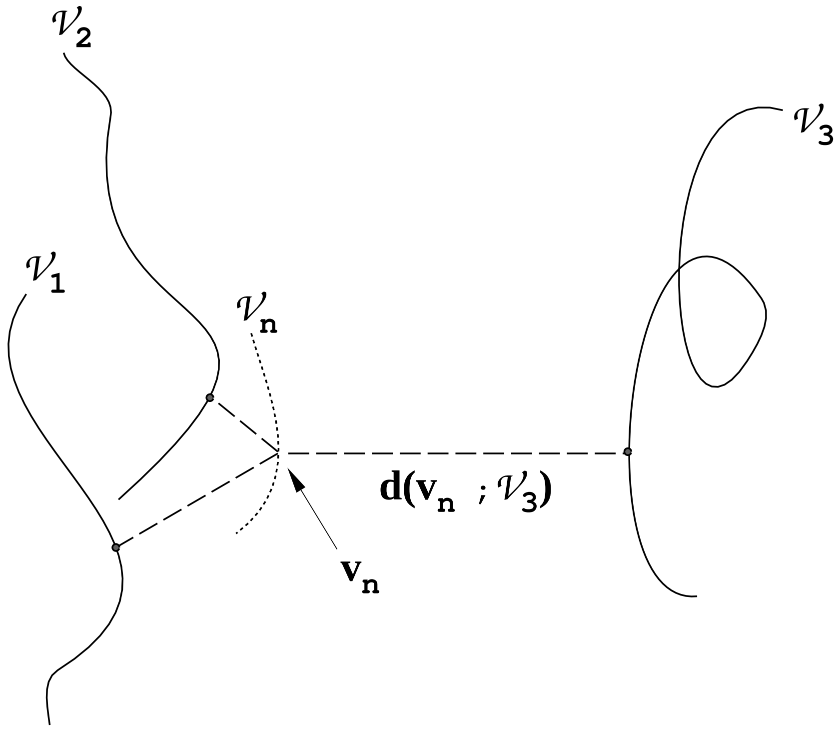
J nu r

I

UNIVERSITY OF

C o n v n
s r p rs

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



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

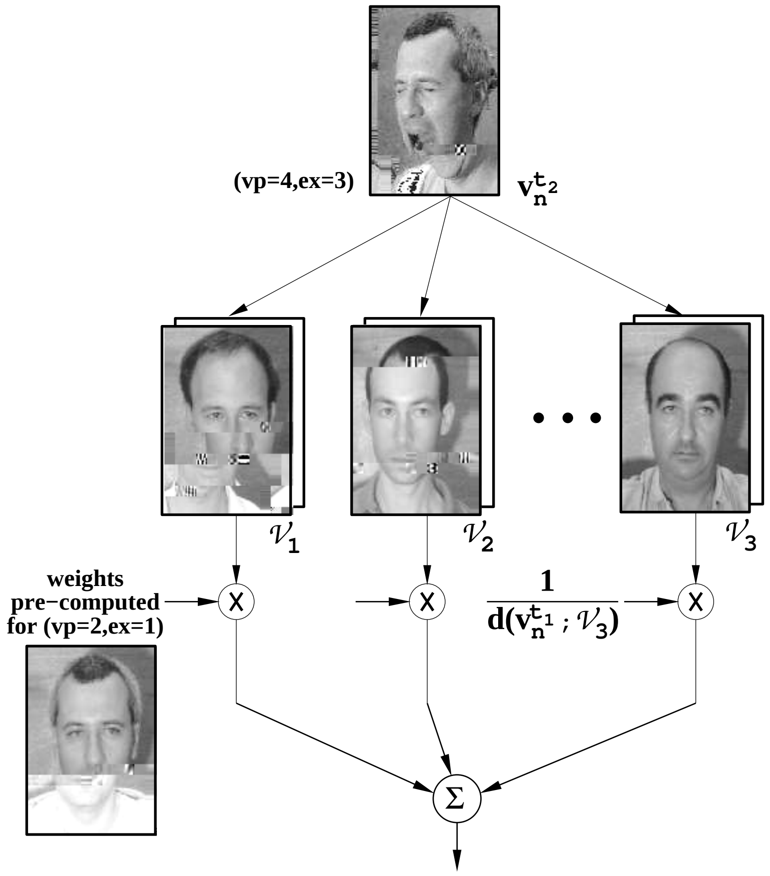


Figure 2: A mechanism for estimating the viewsu12l4072.60e2Tf100-15(thehanism)]a9lA

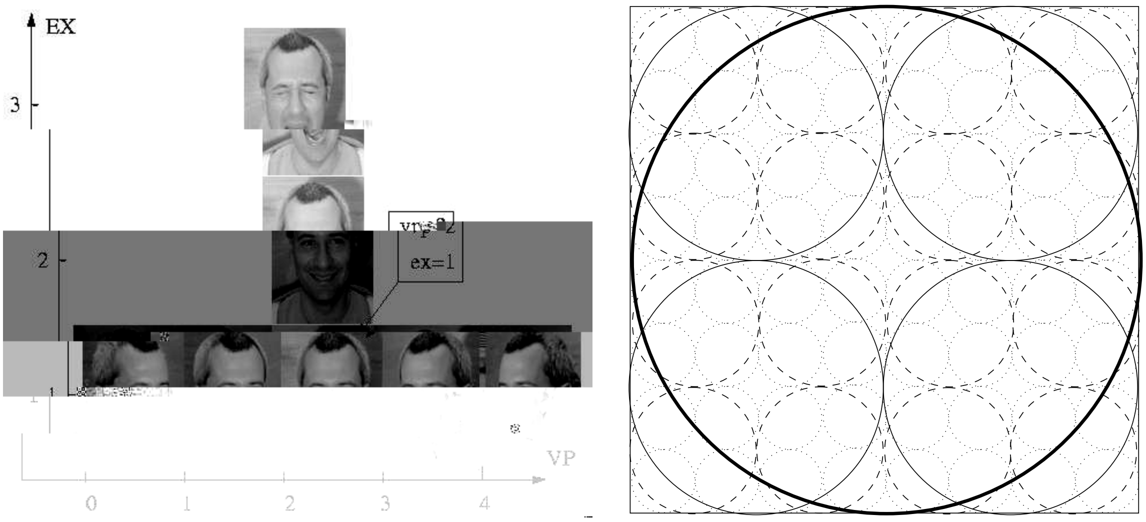


Figure 3: *Left:* the dimensions of variation in the face 4(386)Tj63737.llustr(3[Wcn602.21i95c4[2f[(TTd5c8.5able131287164y695c

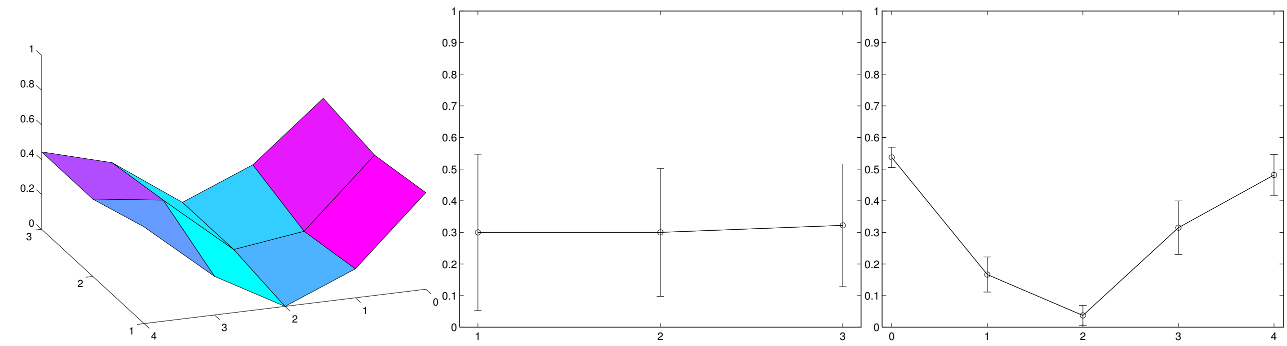


Figure 4: *Left:* a surface plot of the error rate vs. VP and EX (the numbers are listed in Table 1). *Middle:* error rate vs. VP, averaged over the three different values of EX. *Right:* error rate vs. EX, averaged over the five different values of VP. The mean error rate over the five viewing positions (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%).

References

[1] P. Alfeld. c ttered d t interpol tion in three or more v ri bles. In T. Lyche nd L. chum ker, editors, *Mathematical Methods in Computer Aided Geometric Design*, p ges 1–33. Ac demic Press, New York, 1989.

[2] R. B sri. Recognition by prototypes. A.I. Memo No. 1391, Artifici l Intelligence L bor tory, M ss chusetts Institute of Technology, C mbridge, MA, 1992.

[3] R. B sri. Recognition by prototypes. *International Journal of Computer Vision*, 19(147-168), 1996.

[4] D. Beymer nd T. Poggio. Im ge represent tions for visu l le rning. *Science*, 272:190 –1909, 1996.

[ ] . Edelm n nd . Duvdev ni-B r. imil rity-b sed viewsp ce interpol tion nd the c tegoriz tion of 3D objects. In *Proc. Similarity and Categorization Workshop*, p ges 7 –81, Dept. of AI, University of Edinburgh, 1997.

[6] . Edelm n nd . Duvdev ni-B r. imil rity, connectionism, nd the problem of represent tion in vision. *Neural Computation*, 9:701–720, 1997.

[7] W. J. Gordon nd J. A. Wixom. hep rd's method of 'Metric Interpol tion' to biv ri te nd multiv ri te interpol tion. *Mathematics of Computation*, 32:2 3–264, 1978.

[8] A. J. Howell nd H. Buxton. Receptive field functions for f ce recognition. In *Proc. 2nd Int. Workshop on Parallel Modelling of Neural Operators for Pattern Recognition (PAMONOP)*, p ges 83–92, F ro, Portug l, 199 .

[9] M. L ndo nd . Edelm n. Receptive field sp ces nd cl ss-b sed gener liz tion from single view in f ce
6(In)0.0P1.38(Int'Workshop...)Tj18.60Td(.)Tr
ppro c

[13] T. Poggio nd . Edelm n. A network th t le rns to recognize three-dimension l objects. *Nature*, 343:263–266, 1990.

[14] T. Poggio nd T. Vetter. Recognition nd structure from one 2D model view: observ tions on prototypes, object cl sses, nd symmetries. A.I. Memo No. 1347, Artifici l Intelligence L bor tory, M ss chusetts Institute of Technology, 1992.

[1] D. hep rd. A two-dimension l interpol tion function for irregul rly sp ced d t . In *Proc. 23rd National Conference ACM*, p ges 17– 24. ACM, 1968.

[16] . Ullm n nd R. B sri. Recognition by line r combin tions of models. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 13:992–100 , 1991.

[17] T. Vetter nd T. Poggio. Im ge synthesis from single ex mple im ge. In B. Buxton nd R. Cipoll , editors, *Proc. ECCV-96*, number 106 in Lecture Notes in Computer cience, p ges 6 2–6 9, Berlin, 1996. pringer.