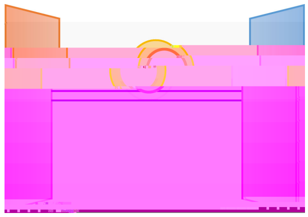

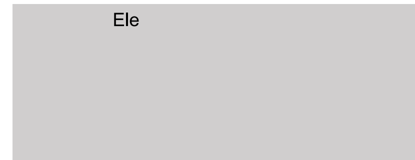
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2) PCA: PCA is the oldest and the most widely used technique in multivariate analysis. PCA uses a linear matrix to transfers data to a new coordinate system . Such transformation causes the projection of the data on the first coordinate to have the largest variance (referred to as first principal component), on the second coordinate to have the second greatest variance, and so on. In this way, PCA produces an array of decorrelated signals ordered in decreasing order of statistical variance. Thus, the goal of PCA is to find the projection matrix that maximizes the variance σ^2, i.e., the 2nd-order (central) moment, of the projected data. Traditionally, PCA can be obtained analytically from singular value decomposition of

TABLE II
ENERGY USE IN TRAINING PHASE

TABLE VI
MODELING PARAMETERS

N-dimension space. We define the centroid of all weight vectors as $_{cen} = \frac{1}{N} {}^{n}_{k=1} \; _{i}$, and define unit vectors $_{max}$, $_{min}$ representing the 1st and Nth PC (or IC) vector directions, respectively. Then, the weight vector $_{min}$ associated with the minimum output variance σ^2 (or kurtosis $kurt$) is updated until all the weight vectors pointing in nearly the same direction at which point the algorithm is converged.

Each iteration consists of four type of main operations: *reflection, expansion, contraction, and shrinkage*. Reflection improves $_{min}$ by simply reversing its direction with respect to $_{cen}$. We get many $^{new}_{min}$

end for

Among $f(\ _i)(i = 1, \ldots, n)$, find $f_{max} = max(f(\ _i))$, $f_{min} = min(f(\ _i))$;

Set $\ _{max} = argmax(f(\ _i))$, $\ _{min} = argmin(f(\ _i))$;

if $|f_{max} - f_{min}| \leq$ **then**

return $\ _1 = \ _{max}$, $\ _2 = \ _1^T$;

end if

while $|f_{max} - fmin| >$ **do**

Compute the centroid of all weight vectors: $\ _{cen} = E(\ _i)$;

Compute the normalized reflected weight vector: $\ _{ref} = \ _{cen} + \beta(\ _{cen} - \ _{min})$;

Compute the normalized whitened reflected weight vector:

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