Artificial Intelligent Collaborative Synchronous in Realtime using High Speed Verify-Identify Tracking Recognition for E-learning

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Abstract— **Collaborative Synchronous e-Learning can provide high levels of interaction for distance learning initiatives. With the rapid evolution of technology, face recognition login and tracking, continuous product evaluation is necessary to ensure optimal methods and resources for connecting students, instructors, and educational content in rich, online learning communities. This article presents the analysis of online, synchronous learning solutions. We are focusing on their abilities to meet technical and pedagogical needs in higher education. To make a solid comparison, the systems were examined in online classrooms with instructors, guest speakers, and students. Relative to usability, instructional needs, technical aspects, and compatibility are outlined for systems. We propose Verify-Identify Tracking Recognition Model for five algorithms. The result of the experiment, $(2D)^2$PCA algorithm can recognize learner's accuracy for Verify-Identify learner 99.46 percentage for 50 learners.**

Keywords- distance learning; collaborative learning; face tracking;

I. INTRODUCTION

In a relatively short amount of time, e-Learning has gained a permanent, highly visible place in the worldwide higher education community. A practice that a few years ago held only a niche role now is an indispensable element of many institutions' curricula, success, and overall reputation. From working adult learners to full-time students living on and off campus to dedicated educators, individuals are increasingly taking advantage of synchronous e-Learning opportunities such as virtual lectures and mentoring, as well as asynchronous e-Learning offerings such as digital online courses, flexible content creation and distribution, and built-in assessment tools.

Collaborative synchronous e-learning is live, real-time and usually scheduled, facilitated instruction and learning-oriented interaction. This research emphasized "learning-oriented interaction" in order to differentiate synchronous learning from lecture, product demonstrations, and other "knowledge dispersal" activities. In opinion backed by plenty of research findings, the interaction is essential to learning. Collaborative synchronous e-Learning is synchronous learning that takes place through electronic means. The synchronous learning field is distinguished from self-paced in every area. e-Learning has grown rapidly to become a significant component in most organizations and training environments. Collaborative e-Learning is live, real-time, interactive, electronically-enabled learning. Synchronous e-Learning sessions can usually be recorded and played back, but that's not their primary strength or purpose. This research focus is on the live and the collaborative.

Although synchronous e-Learning is about utilizing tools to achieve effective training and education, identifying the main categories of synchronous e-Learning technologies is a good place to begin. Even though the rest of this research deals with what we will refer to as the "Web conferencing" category, it is important to differentiate these terms: Teleconferencing and its e-TV Online major sub-categories, audio conferencing and videoconferencing; Webcasting; Simulations; and Web conferencing.

II. CORE ADVANTAGES TO USING FULL EFFICIENCY

Like most successful technology areas, synchronous e-Learning emerged to fill a need and then expanded to provide options previously unavailable to early adopters. The roots of synchronous e-Learning derive from three main influences: the classroom, the media, and the conference. There are plenty of great reasons to adopt synchronous e-Learning approaches.

Determining whether a learning need for synchronous e-Learning exists is rooted in its core definers. Synchronous e-Learning is real-time, interactive, collaborative and participatory, versatile, multi-modal (combining text, audio, video, graphics, etc.), and, most importantly, fun and effective. Some of the key advantages to using Collaborative synchronous e-Learning include:

A. Connecting dispersed learners

Synchronous methods are especially well suited to organizations with geographically distributed learning populations. For instance, you may have a nationwide audience of regional representatives who need updating on product features and enhancements. Firms with telecommuters and remote learners will also realize tremendous advantages.

B. Real-time interaction and collaboration

Synchronous tools allow us to engage with other audience in real time, a very natural process that permits a spontaneous and flowing learning session. Answers to questions are immediate and clarification can be provided directly. Synchronous tools also lend themselves well to structured collaborative assignments. The social dimension of synchronous tools creates a learning synergy.

C. Sense of immediacy and co-presence

Synchronous tools are ideal for conveying late-breaking and time sensitive information. Since the human presence is so "front and center" when using these tools, the warm learner experience that is generated allays anxieties about the mechanical or depersonalized nature of technology-enabled learning.

D. Fostering a learning community

Learners benefit from sharing ideas and experiences with their colleagues. A major advantage to synchronous e-Learning tools is the development of a sense of connectedness and community among learners. Long term impacts can include better teamwork and collaboration skills, improved employee retention, stronger morale, and the formation of a collective identity More generally, the variety process of tools and communication choices available in synchronous e-Learning provides numerous options for connecting with diverse learners with different learning styles.

E. Balancing learning dynamics

Synchronous e-Learning can reduce imbalances and create a more egalitarian learning experience. It can avoid the power dynamics of the face-to-face learning environment, where extroverts can dominate and where gender and other personal identifiers can impact group activities. Used effectively, synchronous e-Learning tools can overcome some of those barriers and level the field. The use of anonymous feedback tools can increase the comfort level of online participants by reducing the fears that adult learners often have around answering incorrectly in front of their peers. More generally, the variety of tools and communication choices available in synchronous e-Learning provides numerous options for connecting with diverse learners with different learning styles.

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F. Unique functionality

Many synchronous e-Learning tools include features and functionality that offer unparalleled opportunities for fast and effective learning. Whiteboarding tools can permit class exercises that can be easily saved and recalled. Application sharing allows for rapid and easy group work. Web tours can guide learners to specific points of interest.

G. Extending application demonstrations

Provide software and desktop learning can benefit tremendously from the real-time application demonstration features of synchronous tools. Many tools also provide integrated virtual lab components, permitting supervised simultaneous practice sessions

H. Synthesizing materials and concepts

Process-oriented tasks and information-heavy materials are best taught through asynchronous, on-demand training or reference materials. But the collaborative nature of synchronous tools makes them well suited to permitting learners to synthesize complex ideas. Synchronous e-Learning provides an online means for group learning techniques through discussions and dialogue, problem-solving exercises, and thoughtful reflection.

III. ACTIVITY CONNECTION TO COMPLETE SYSTEM

The audio conference calls and conferencing tools both are support effective instructional methods to appeal to a wide variety of learning styles. The functions available and a few of their collaborative synchronous e-learning uses are:

1) A slide or file display that allows the instructor to show students PowerPoint slides or other files.
2) A whiteboard to brainstorm a list of ideas
3) Application sharing, so the instructor can do a software demonstration from one computer that can be seen by every attendee.
4) Tool access, so the instructor can share the ability to use tools and functions of the online interface with students or other instructor.
5) Peer-to-peer Chat, to get students to connect with other students.
6) Instant feedback , to confirm the appropriateness of the pace and the content.
7) Annotation, to focus students' attention on a specific area of the screen.

A. Log-in with face recognition

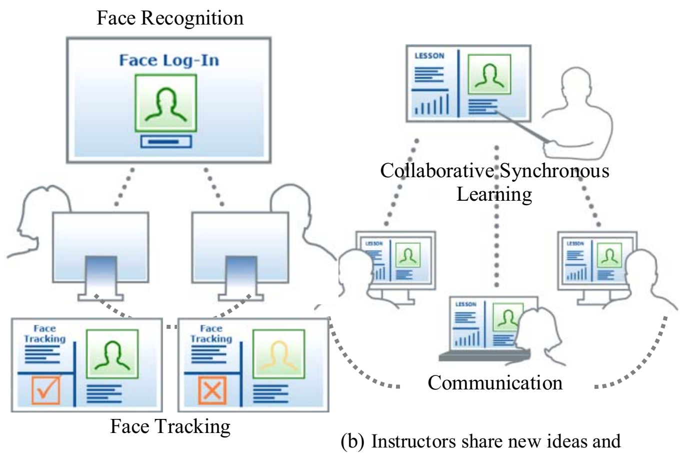
Using only a browser, students and presenters can attend their Synchronous e-Learning on the Web by face recognition log-in and face tracking to access learns the content and multimedia.

B. Slide or display file

Instructor and Audience can use slides to help organize their content for presentation and to manage the flow of ideas. Bulleted lists, graphs, photographs, and screen captures help participants follow along. Often, by using this feature the instructor can also show sample documents created in Word, Flash, or HTML format. In fact, most products let you use the slides you already have, and they may support custom animations in PowerPoint. Another use of slides is similar to the advertising and trivia shown at movie theaters before the lights are turned down and the preview clips begin.

C. Whiteboard

With a whiteboard, instructors can encourage students to share ideas and comments through brainstorming, ask questions, and type their responses on the whiteboard. This promotes interaction, validates student input, and provides clarification for others who may not have heard the answers. The instructor can also use the whiteboard to sketch or annotate.



(a) Face recognition log-in and face tracking.

(b) Instructors share new ideas and information with learners, on student performance, providing guidance and feedback on student performance.

Figure 1. Solutions of Intelligent Collaborative Synchronous e-Learning.

D. Tool access and sharing

The leader or leaders of the session control the images and tools that all online participants see. They can display files, annotate important points, and create quizzes slides. Students can contribute verbally, but cannot control the tools. You, or the training coordinator who sets up the session, can select the access level for each of the invitees so that two or more instructors can take turns delivering. There are also options that give all participants (almost) equal control. The research methodology of the E-Leanring P3 Development and Delivery Model consisted of two sections: Content Development and Content Delivery.

IV. Identify Realtime By Learner Recognition

A. Weighted Pairwise Scatter Coupled Subspace Linear Discriminant Analysis

We uses Weighted Pairwise Scatter Coupled Subspace Linear Discriminant Analysis (WPS-CSLDA) algorithm in pattern recognition of face tracking. Theory of Linear Discriminat Analysis of data group will be considered. Many problems encountered in determining the Group is to mingle the different groups of information. In the next section will bring the theory to the solution of this mingling of the theory have a Weighted Pairwise Scatter. Concept of Weighted Pairwise Scatter; The general LDA theory, In the first term

$$\bar{S}_W = W^T S_W W \tag{1}$$

will be Called matrix distribution within the group. And the second term

$$\bar{S}_B = W^T S_B W \tag{2}$$

will be Called matrix distribution between the groups. If W is linear projection in the new feature space, the distribution within and between groups will be and concept of LDA, get the distribution matrix ratio between the matrix and matrix distribution in the group after transform is the most. Enabling a data conversion is still the most discrimination, while the dimension size will decrease. We want to make the objective function:

$$\frac{Max}{W}\frac{\left|W^T S_B W\right|}{\left|W^T S_W W\right|} \tag{3}$$

The answer to solve this problem use Eigenvector that the value correspond which Eigenvalue to sort descending from the equation:

$$S_B W = \lambda S_W W \tag{4}$$

patterns of matrix distribution between the groups can be obtained from

$$S_B = \sum_{i=1}^{L} N_i(\bar{t}_i - \bar{t})(\bar{t}_i - \bar{t})^T \tag{5}$$

Assigned S_B is matrix distribution between the groups.

$\bar{t}$ is the average of all samples.

$\bar{t}_i$ is average sample of each group.

This equation is calculated that how to divide the average data in each group from the center of data. It is good to have the much of S_B. Because it shows whether the various are widely separated from transformed space, but the equation cannot shows clearly that the various groups will be excluded. The following example will illustrate this point to consider.

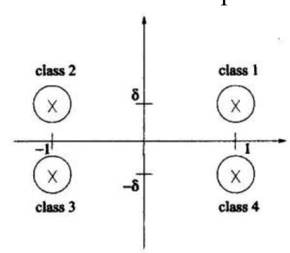


Figure 2. Example Assigned to four Data groups of WPS-CSLDA which has equal variance at differenct positions

Example Assigned to four groups, each group contains a number of feature vectors are identical and equal variance, from figure 1 is shown.

$$\bar{t}_1 = (1,\delta),\ \bar{t}_2 = (-1,\delta)\ \bar{t}_3 = (-1,-\delta),\ \bar{t}_4 = (1,-\delta)$$

This problem is shown in Figure 1 in this case, the spread between the metrics as follows. Assigned $\delta = 0$

$$\frac{1}{4}S_B = \begin{pmatrix} 1 & 0 \\ 0 & \lambda \end{pmatrix} \rightarrow \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \tag{6}$$

Metric distributions between the groups are not separated in the vertical. But them can extract in horizontal only. We can tell you that the variance of other couple data groups will influence with matrix distribution between groups over (1,4) and (2,3) to consider the issue in a separate group variance of couple data groups (1,4) and (2,3) is more important than the other. Because this couple data groups are complicated rather than distribution between uncapture information groups. In above example shows that if some information groups nearby to compare with other groups. Matrix distribution between groups in the majority ignores the distinction between information that is near the same. To maintaining sufficient information to discriminate. Must be adjusted to weight, the adjustment which accepted is adjust weight equal to inverse and Euclidean distance of the mean difference between groups.

$$\varpi = \frac{1}{\left\|(\bar{t}_i - \bar{t})\right\|} = \frac{1}{(\bar{t}_i - \bar{t})^T (\bar{t}_i - \bar{t})} \tag{7}$$

We will focus on data group which the average near to other groups than the average group apart. In this case, the group are mingling of data will be more and more interest groups are mingling of less data will be less interested. Due to the normal pattern of weight, matrix distribution between groups will be

$$S_{B_{norm}} = \frac{1}{N_i} \sum_{i=1}^{L} N_i \frac{(\bar{t}_i - \bar{t})(\bar{t}_i - \bar{t})^T}{(\bar{t}_i - \bar{t})^T (\bar{t}_i - \bar{t})} \tag{8}$$

In the example of the problem. Inverse between groups were calculated by (B) is as follows. Assigned $\delta = 0$.

$$\frac{1}{4} S_{B_{norm}} = \begin{pmatrix} 1 + \dfrac{1}{1+\delta^2} & 0 \\ 0 & 1 + \dfrac{\delta^2}{1+\delta^2} \end{pmatrix} \rightarrow \begin{pmatrix} 2 & 0 \\ 0 & 1 \end{pmatrix} \tag{9}$$

Therefore, the matrix of variance between groups (B) does not happen with the one near each of the pairs (1,4) and (2,3), we will spread it in the calculation of WPS-CSLDA must be required due to separate data problem. When we distributed among the new matrix. We will solve the equation of distribution between groups by the new addition to the matrix remains the same. Calculation feature of WPS-CSLDA; Assigned a core of screening $U \notin \Re^{mxr}$ and $V \notin \Re^{nxc}$ A picture size is m x n from projection A on core U and V following the principles of linear transformation.

$$Y = U^T A V \tag{10}$$

So the Y is a matrix feature of image sizes rxc where $r < m$ and $c < n$ When set to sample all images are M and the number of groups are L, each the number of images in N_i images, Each image that teaching size is mxn, A_j (j=1,2,…,M) The average of all images are $\bar{A}$ and $\bar{A}_i$(i=1,2,…,L) is the average of each image in P_i group is projected group. After the image has been projected on U and V axis the matrix feature can be

$$Y_j = U^T A_j V, j = 1,2,...,M \tag{11}$$

How to find the axis of projection U and V can be calculated by determining trace of the matrix covariance of image samples are screening, this idea can create to equation is.

$$J(U,V) = \frac{P_B}{P_W} \tag{12}$$

When $P_B = tr(\tilde{S}_B)$

$P_W = tr(\tilde{S}_W)$

$\bar{S}_B$ is the matrix distribution between group of the preview was screening.

$\bar{S}_W$ is the matrix distribution in group of the preview was screening.

$$\tilde{S}_B = \sum_{i=1}^{L} \varpi N_i (\bar{Y}_i - \bar{Y})(\bar{Y}_i - \bar{Y})^T \tag{13}$$

$$= \sum_{i=1}^{L} \varpi N_i [(\bar{A}_i - \bar{A})V][U(\bar{A}_i - \bar{A})V]^T$$

$$\tilde{S}_W = \sum_{i=1}^{L} \sum_{Y_k \in P_i} (Y_k - \bar{Y}_i)(Y_k - \bar{Y}_i)^T \tag{14}$$

$$= \sum_{i=1}^{L} \sum_{Y_k \in P_i} [U(A_k - \bar{A}_i)V][U(A_k - \bar{A}_i)V]^T$$

In case

$$tr(\tilde{S}_B) = tr(\sum_{i=1}^{L} \varpi N_i U^T (\bar{A}_i - \bar{A}) V V^T (\bar{A}_j - \bar{A})^T U) \tag{15}$$

$$tr(\tilde{S}_W) = tr(\sum_{i=1}^{L} \sum_{Y_k \in P_i} U^T (\bar{A}_k - \bar{A}_i) V V^T (\bar{A}_k - \bar{A}_i)^T U) \tag{16}$$

When ϖ is the weighted pairwise scatter , Next step to calculate U and V can not simultaneously. Therefore, by calculating the value, according to $V=1$ (identity matrix) to determine the sequence of U to $U=1$ calculate the value of V to calculate U. Assigned $V=1$

$$tr(\tilde{S}_B) = U^T S_B^U U, tr(\tilde{S}_W) = U^T S_W^U U \tag{17}$$

$$\tilde{S}_B^U = \sum_{i=1}^{L} \varpi N_i (\bar{A}_i - \bar{A})(\bar{A}_i - \bar{A})^T \tag{18}$$

$$S_W^U = \sum_{i=1}^{L} \sum_{Y_k \in P_i} (\bar{A}_k - \bar{A}_i)(\bar{A}_k - \bar{A}_i)^T \tag{19}$$

Form equation (19) can substitute a new one.

$$J(U) = \frac{U^T S_B^U U}{U^T S_W^U U} \tag{20}$$

To solve the equation for U in the optimal screening, can do this by finding the best of $J(U)$.

$$U_{opt} = \arg \max_{U} J(U) \tag{21}$$

If S_W^U is not non singular matrix, can be calculated U_{opt} by Eigenvector and Eigenvalue from the equation.

$$S_W^U U_{opt} = \lambda S_W^U U_{opt} \tag{22}$$

Typically, the optimal projection axes used in the projection from the Eigenvector of $S_W^{U-1} = S_B^U$ associated with the largest of Eigenvalue from to m, but in fact, because looking features of the image. Therefore a core of projection be selected from to r only, so new matrixs used in the projection has a size mxr.

$$U = [u_1 u_2 .. u_r] \tag{23}$$

To calculate V, Assigned $U=1$ (1 is identity metric), then the same calculations for all U of equation (8) to (12) by changing variables U as V. WPS-CSLDA Method, can bring matrix features and the optimal projection axis U and V to create a new steps. Assigned to A, where Y is a picture of the image matrix feature A, where $U = [u_1 u_2 ... u_r]$ and $V = [v_1 v_2 ... v_c]$ is the optimal projection axis. So the equation is creating a new image which represent of face recognition.

$$\tilde{A} = UYV^T \quad (22)$$

B. Principle Component Analysis Algorithm

Principal component analysis (PCA) is a mathematical procedure that uses anorthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables. PCA is sensitive to the relative scaling of the original variables. Depending on the field of application, suppose $x_1, x_2, ..., x_M$ are *Nx1* vectors

$$\bar{x} = \frac{1}{M}\sum_{i=1}^{M} x_i \quad (23)$$

By subtract the mean: $\Phi_i = x_i - \bar{x}$ (24)

Operation form the matrix $A = [\Phi_1 \Phi_2 ... \Phi_M]$ (NxM matrix)

$$C = \frac{1}{M}\sum_{i=1}^{M} \Phi_n \Phi_n^T = AA^T \quad (25)$$

Dimension of data will compute to eigenvalues of C:

$\lambda_n > \lambda_n > ... > \lambda_N$ by eigenvectors of C: $u_n, u_n, ..., u_N$ (26)

Since C is symmetric $u_n, u_n, ..., u_N$ form a basis

$$x - \bar{x} = b_1 u_1 + b_2 u_2 + ... + b_N u_N = \sum_{i=1}^{N} b_i u_i \quad (27)$$

The variable will keep only the terms corresponding to the K largest eigenvalues:

$$x - \bar{x} = \sum_{i=1}^{K} b_i u_i \quad \text{where } K << N \quad (28)$$

The representation of $x - \bar{x}$ into the basis $u_n, u_n, ..., u_K$

C. Two Dimension Principle Component Analysis Algorithm

Consider an m by n random image matrix A. Let $X \in R^{nxd}$ be a matrix with orthonormal columns, $n \geq d$. Projecting A onto X yields an m by d matrix $Y = AX$. In 2DPCA, the total scatter of the projected samples was used to determine a good projection matrix X. That is, the following criterion is adopted:

$$\begin{aligned} J(x) &= trace\{E[(Y - EY)(Y - EY)^T]\} \quad (29) \\ &= trace\{E[(AX - E(AX))(AX - E(AX))^T]\} \\ &= trace\{X^T E[(A - EA)^T (A - EA)]X\} \end{aligned}$$

where the last term in this equation as results from the fact that trace (AB) = trace (BA), for any two matrices .When *image covariance matrix* $G = E[(A - EA)^T (A - EA)]$, which is an n by n nonnegative definite matrix. Suppose that there are M training visual images, denoted by m by n matrices $A_k (k = 1, 2, ...M)$, and denote the average image as

$$\bar{A} = \frac{1}{M}\sum_k A_k . \quad (30)$$

Then G can be evaluated by

$$G = \frac{1}{M}\sum_{K=1}^{M} (A_k - \bar{A})^T (A_k - \bar{A}) \quad (31)$$

It has been proven that the optimal value for the projection matrix X_{opt} is composed by the orthonormal eigenvectors of $X_1, ..., X_d$ of G corresponding to the d largest eigenvalues. Because the size of G is only n by n, computing its eigenvectors is very efficient. Also, like in Principle Component Analysis the value of d can be controlled by setting a threshold as follows;

$$\left(\sum_{i=1}^{d} \lambda_i / \sum_{i=1}^{n} \lambda_i\right) \geq \theta \quad (32)$$

where $\lambda_1, \lambda_2, ..., \lambda_n$ is the n biggest eigenvalues of G and θ is a pre-set threshold.

D. Alternative Two Dimension Principle Component Analysis Algorithm

$$A_k = [(A_k^{(1)})^T (A_k^{(2)})^T ... (A_k^{(m)})^T]^T$$

$$\text{and } \bar{A} = [(\bar{A}^{(1)})^T (\bar{A}^{(2)})^T ... (\bar{A}^{(m)})^T]^T \quad (33)$$

where $A_k^{(1)}$ and $\bar{A}^{(i)}$ denote the i-th row vectors of A_k and $\bar{A}$ respectively.

$$G = \frac{1}{M}\sum_{K=1}^{M}\sum_{i=1}^{m} (A_k^{(i)} - \bar{A}^{(i)})^T (A_k^{(i)} - \bar{A}^{(i)}) \quad (34)$$

This equation reveals that the image covariance matrix G can be obtained from the outer product of row vectors of images, assuming the training images have zero mean. $\bar{A} = (0)_{mxn}$ For that reason, we claim that original of Alternative Two Dimension Principle Component Analysis Algorithm is working in the row direction of images. A natural extension is to use the outer product between column vectors of images to construct G.

$$A_k = [(A_k^{(1)})(A_k^{(2)})...(A_k^{(m)})] \text{ and}$$

$$\bar{A} = [(\bar{A}^{(1)})(\bar{A}^{(2)})...(\bar{A}^{(m)})] \quad (35)$$

where $A_k^{(j)}$ and $\bar{A}^{(j)}$ denote the j-th column vectors of A_k and $\bar{A}$ respectively. Then an alternative definition for image covariance matrix G is:

$$G = \frac{1}{M}\sum_{k=1}^{M}\sum_{j=1}^{n} (A_k^{(j)} - \bar{A}^{(j)})(A_k^{(j)} - \bar{A}^{(j)})^T \quad (36)$$

Next,we will show how equation can be derived at a similar way as in Alternative Two Dimension Principle Component

Analysis Algorithm. Let $Z \in R^{mxq}$ be a matrix with orthonormal columns. Projecting the random matrix A onto Z yields a q by n matrix $B \in Z^T A$. The following criterion is adopted to find the optimal projection matrix Z as

$$J(Z) = trace\{E[(B - EB)(B - EB)^T]\} \quad (37)$$
$$= trace\{E[(Z^T A - E(Z^T A))(Z^T A - E(Z^T A))^T]\}$$
$$= trace\{E[(Z^T E(A - EA)(A - EA)^T]Z\}$$

From this equation will alternative definition of image covariance matrix G is :

$$G = E[(A - EA)(A - EA)^T] = \frac{1}{M}\sum_{k=1}^{M}(A_k - \overline{A})(A_k - \overline{A})^T \quad (38)$$

$$G = \frac{1}{M}\sum_{k=1}^{M}\sum_{j=1}^{M}(A_k^{(j)} - \overline{A}^{(j)})(A_k^{(j)} - \overline{A}^{(j)})^{(T)}$$

The optimal projection matrix Z_{opt} can be obtained by computing the eigenvectors $Z_1,\ldots,Z_q$ of this equation corresponding to the q largest eigenvalues. $Z_{opt} = Z_1,\ldots,Z_q$ The value of q can also be controlled by setting a threshold. Because the eigenvectors of Equation only reflect the information between columns of images, we say that the alternative 2DPCA is working in the column direction of images.

E. Double Two Dimension in Principle Component Analysis Algorithm

$(2D)^2$PCA and alternative 2DPCA only works in the row and column direction of images respectively. $2D^2$PCA learns an optimal matrix X from a set of training images reflecting information between rows of images, and then projects an m by n image A onto X, yielding an m by d matrix $Y=AX$ Similarly, the alternative 2DPCA learns optimal matrix Z reflecting information between columns of images, and then projects A onto Z, yielding a q by n matrix $B=Z^T A$. In the following, we will present a way to simultaneously use the projection matrices X and Z Suppose we have obtained the projection matrices X and Z projecting the m by n image A onto X and Z simultaneously, yielding a q by d matrix C

$$C = Z^T AX \quad (39)$$

The matrix C is also called the coefficient matrix in image representation, which can be used to reconstruct the original image A , by

$$A = ZCX^T \quad (40)$$

When used for face recognition, the matrix C is also called the feature matrix. After projecting each training image $A_k (k = 1, 2, ...M)$ onto X and Z, we obtain the training feature matrices $C_k (k = 1, 2, ...M)$. Given a test face image Here the distance between C and C_k is defined by

$$d(C, C_k) = \|C - C_k\| = \sqrt{\sum_{i=1}^{q}\sum_{j=1}^{d}(C^{(i,j)} - C_k^{(i,j)})^2} \quad (24)$$

V. RESULT OF THE EXPERIMEMT

There are numerous advantages to adopting synchronous e-Learning, there are also challenges and limitations to consider. These range from the logistical to the pedagogical to the logical. The identification and verification are part of e-Learning Quality Assurance in online learning. This system has a capability to recognize the face of learner with high accuracy. We used 50 video clips in learner's face as sample, it has been random check 3 images per minute in order to verify the learner. Learners' faces have to similar with the image that already registered in the first step. The result of the experiment, $(2D)^2$PCA algorithm can recognize learner's Accuracy face 99.46 percentage for 50 learners.

VI. CONCLUSION

Table 1. Result of experimental for Verify-Identify tracking recognition for human in e-learning.

Method	Accuracy(%)	Dimension	Time(s)
WPS-CSLDA	98.39	98	1.87
PCA	94.5	87	15.23
2DPCA	96.0	26 x 70	2.34
Alternative 2DPCA	97.5	34 x 70	2.36
$(2D)^2$PCA	99.46	12 x 18	1.25

Building and delivering online events takes a lot of preparation, but with practice, instructor can create excellent and effective learning experiences. Collaborative exercises can help get over the problem of a heterogeneous audience by letting the experts within student teams shine. But in general, the intelligent collaborative synchronous e-learning has a hard time on its own handling diverse and complex tasks that require contemplation. We can Verify-Identify tracking face recognition to in front of monitor with $(2D)^2$PCA, Students do not have substitute for learning ,test online, activity online. It make believe about quality of e-Education.

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