Using Principal Component Analysis for Investigation of Multiple Object Tracking

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Abstract

The paper discusses the use of principle component analysis for investigating the influence of mean speed of object tracking and mean set-size of objects in multiple object tracking. The results are based on an experiment with a group of participants tracking subsets of multiple moving or static objects. The goal was to extract the important information from the initial data and to represent it as a set of new variables (principal components) useful for results interpretation.

Keywords: multiple-object tracking, principal component analysis, pair-wise correlations

1 Introduction

In a fast developing society, people are constantly keeping their attention on many moving targets at the same time (e.g. while driving a car, crossing a street, playing video games or team sports etc.). Thus, it is very important to be able to track multiple moving objects through space and time. The multiple object tracking
(MOT) capability can be assessed by different factors, such as visual short term memory (VSTM) and concentration.

In the paper, an assessment of traceability and recognition of multiple tracking of moving objects is done. The objects are designated as targets, tracked while moving through identical distractors.

The collected data are investigated using principal component analysis with SPSS [14, 15]. The method summarizes and uncovers any patterns in a set of multivariate data by reducing the data complexity.

The analysis of the principal components includes mathematical procedures, transforming a number of correlated variables into a smaller number of uncorrelated variables (principal components). In the current study, it is used to analyse the dependence between mean speed for group of objects and stationary objects memorized across group of participants. A staircase procedure was employed in order to determine each participant’s speed for different set-sizes, and number of stationary objects memorized, using a predefined level of accuracy.

2 Multiple-object tracking in the psychological experiments

MOT is the process of location of multiple objects over time in a video stream. It is used to investigate a wide range of topics in visual cognition. Pylyshyn and Storm (1988) were the first experimenters who suggested using the MOT to test the influential of stress on people’s attention (MOT task) [21].

Previous studies used MOT tasks for determination of what counts as an object for object-based attention [22], age differences in attention [27], the dynamics of attention in depth [28] and the coordinate systems underlying attention [5]. This way, an accurate tracking and identification of targets occurs, even when location information changes.

A study by Clair et al. (2010) provided further support for this model by asking participants to track three or four out of ten squares with random-dot texture on a background with the same type of texture. The square-texture motion, speed and direction varied through trials. Results showed that, compared to the static texture condition, tracking performance was worse as the difference between the texture direction and the object direction increased. This was explained by a tracking mechanism integrating the local motion about a target over discrete time intervals to predict future target location [6].

Pylyshyn (1989) suggested a FINST (FINgers of INSTantiation) model which focuses on low-level visual processing by pointing out objects, which have a total of four or five independent indexes assigned to them [20]. The number of indexes or pointers is limited due to the fixed-architecture model, which proposes that the tracking speed for one to four objects is the same. It starts declining for five and more objects [3, 21].

However, Alvarez and Franconeri (2007) conducted an experiment based on MOT, where participants were instructed to track from one to eight out of a total of sixteen objects, at top tracking speeds. The results showed that the tracking speed
was inversely proportional to the number of targets (set-size) tracked. Consistent with a *flexible-resource model* – as set-size increased, the amount of resources devoted to every target decreased, reducing the speed of tracking [3, 4, 12, 18, 26].

Franconeri et al. (2008) suggested that speed alone does not affect tracking performance [8]. An accurate tracking of indefinite number of objects at high speeds, as for tracking one target, was possible after removing crowding effects [9]. Also, Bettencourt and Somers (2009) suggested that attention resources are deployed to both enhancing targets and inhibiting distractors, in order to avoid crowding effects [4]. Doran and Hoffman (2010) found the same results for attention resources in VSTM [7].

Pylyshyn and Storm (1988) suggested a link between global attention and resource limitation because of the drop in accuracy with increased set-size [21]. According to Howe et al. (2010), the accuracy for tracking multiple moving visual objects is the same for tracking moving and static objects [13]. Hence, tracking and VSTM, referred to as attention when speed is zero, are closely linked. The memory and the attention show parallel capacity limits [5]. VSTM capacity depends on various factors, such as age [10], previous experience [23], the nature and complexity of objects [30] and how they are ordered in perception. This strongly suggests that VSTM is limited by some resources that are flexibly allocated.

Wilken and Ma (2004) found that for the static condition as the set-size held in VSTM increases, the precision of the stored information decreases [29]. This might be due to individual differences in VSTM capacity [25].

Green and Bavelier (2006) compared the performance of video game players to non video game players on the MOT paradigm and found that video game players performed better when tracking multiple objects. However, the non video game players increased their tracking capacity after playing video games for a while. The results indicated that playing video games increased the set-size that could be accurately tracked [11]. Allen et al. (2004) tested experts and novices on the MOT task, and found that experts outperformed novices. This suggests that expertise can increase the set-size tracked [2].

There are many factors influencing the VSTM, thus several laboratory-based experiments continue to be conducted in order to test MOT in different conditions and the relations with other memory parameters.

### 3 Experiment

**Participants**

Data in the experiment were collected from sixty eight participants (34 men and 34 women), aged between 19 and 40 years. All of them were healthy and reported normal or corrected-to-normal vision.

The mean and standard deviation of the group’s age are $\overline{x} = 26.161$ and $s = 3.958$. Data for three of the participants was excluded because their age was
out of the interval \((\bar{x} - 3s, \bar{x} + 3s) = (14.287, 38.036)\). Finally, the number of participants considered is \(n = 66\).

**Experimental equipment**

The experiment was carried out on a computer with 19 inch CRT monitor and using MatLab. The program allowed vision researchers to display stimuli quickly and to get precise control over the timing of the stimulus.

The participants were seated in a dimly lit room at a distance of 60 cm from the monitor, being required to wear headphones.

**Stimuli**

Twenty-four \((l = 24)\) identical round yellow disc-shaped (0.645° Visual Angle, VA in radius each) objects, surrounded by an invisible “bumper” each (0.99° VA in radius) and a black central fixation cross (1.128° x 1.128° VA) were shown on a white background of the display. The “bumpers” allowed objects to bump at each other and to bounce off the edges of the screen.

**Procedure**

At the start of each trial, all \(n = 24\) objects were displayed on the screen. A subset of \(l, l_i < l, i = \overline{1,4}\) objects was selected as targets and others \(d_i = l - l_i, i = \overline{1,4}\) objects – as distractors. Four cases were considered:

- **1\textsuperscript{st} case**: \(l_1 = 2\) moving targets and \(d_1 = 22\) distractors;
- **2\textsuperscript{nd} case**: \(l_2 = 4\) moving targets and \(d_2 = 20\) distractors;
- **3\textsuperscript{rd} case**: \(l_3 = 6\) moving targets and \(d_3 = 18\) distractors;
- **4\textsuperscript{th} case**: \(l_4 = x\) static targets consequently from \(x = 8\) to 12 and \(d_4 = l - l_4\) distractors respectively.

The participants had to complete a minimum of one training block, consisting of 10 trials, in order to understand and familiarize with the task. There were 4 blocks, each consisting of 32 trials. A short break was done after each block and an on-screen performance feedback in percentages was given. It took approximately 30 minutes to complete the experiment which means that one trial continues approximately 14 seconds.

*In the first three cases, each trial included the following steps:*

- the participants were asked to keep their eyes focused on the central fixation cross on the screen with all objects;
- depending on the case, at the start of each trial, the relative subset of objects (targets) were cued by a black dot in the middle for 3 sec;
- after that the black dots disappeared and all objects started moving linearly at random direction for 5 sec, while increasing their speed during the first 0.4 sec;
- after the objects stopped moving, two random objects were sequentially cued for 2 sec;
- participants had to identify each of the two targets as either an initially cued object, a target by pressing “t”, or a distractor, by pressing “d” on the computer keyboard. The response was considered as correct only if both cued objects had been classified correctly;
- visual and auditory feedback was provided after each trial: the auditory feedback consisted of a 0.2 sec beep that was high for correct responses and low for incorrect responses, and the visual feedback which was green for the correct and red for incorrect responses;
- if the both cued objects were identified correctly, the speed of the objects movement for the following trial was increased and the sound was increased with 1dB, whereas if only one of the cued objects was identified correctly, then the speed was decreased and the sound was decreased with 2dB. The mean speed for a block was used as a measure of the mean sound level (dB);
- there was a 1 sec break between trials.

The fourth static case included as follows:
- the trials began with 8, 9, 10, 11 or 12 objects cued by a black dot for 3 sec;
- all objects turned yellow and remained in their initial unsystematic positions for 5 sec;
- sequential cueing of two random objects followed for 2 sec at the end;
- the identification of objects and feedback were the same as in the previous three cases.
- if both cued objects were identified correctly (high tone and coloring in green), the number of target objects for the next trial was increased by one. If even one of the cued objects was not recognized correctly (low tone and coloring in red), then the number of target objects for the next trial was reduced by two (but remaining not less than 8).

4 Calculations, data analysis and results

The calculations and analysis of the experiment’s data were made with one of the most used multivariate statistical technique PCA by SPSS [17]. PCA analyses the initial data set $x_1$, $x_2$,...,$x_m$ of the $m$ original correlated variables, each with $n$ observations (measurements). Its goal is to extract the important information from the data in order to represent it as a reduced set of new $k$ ($k \leq m$) uncorrelated $n$-dimensional variables (principal components) $c_1$, $c_2$,...,$c_k$, accounting for most of the variance in the $m$ variables. This is achieved by reducing the dimensionality of the initial space through the setting of a new basis of components which are orthogonal or inclined. PCA does not ignore correlations, it concentrates on variances. The transformation is defined in such a way that the first principal component has the largest possible variance and each following component in turn has the highest possible variance under the constraint that it is orthogonal to the preceding components. The other components are computed likewise [1, 14, 15, 16, 24].
Each \(i^{th}\) principal component is expressed as a linear combination of the variables, thus
\[
c_i = w_{i1}x_1 + w_{i2}x_2 + \ldots + w_{im}x_m, \quad i = 1, k
\]
or in matrix form
\[
Y = WX
\]
where \(X \in \mathbb{R}^{n \times m}\) - matrix of original variables, \(Y \in \mathbb{R}^{k \times m}\) - matrix of principal components, \(W \in \mathbb{R}^{k \times n}\) - matrix of weight coefficients chosen that the required maximal variance and uncorrelated conditions hold.

The results of PCA are usually discussed in terms of component loadings and component scores. Component loadings can be interpreted as the correlation between an observed variable and a component or as the weight by which each standardized original variable should be multiplied to get the component score. Component scores are the transformed variable values corresponding to the initial data. They can be interpreted geometrically as the projections of the observations into the principal components.

In order to obtain an adequate PCA model, the initial data need to satisfy following requirements: random character, numerical type, independent data correlated with each other, normal distribution, volume bigger than 50 and data corresponding to the adequacy conditions. These are fulfilled in the current experiment. In Figure 1, the mean speeds of the moving targets (original variables: 2-targets, 4-targets and 6-targets) and mean set-size of the static targets (original variable: \(x\)-targets) depending on the number of targets in each subset are illustrated. The descriptive statistics of the 4 variables is given in Table 1. The results showed that as the number of targets increased, the mean speed at which they could be accurately tracked decreased. The mean number of targets remembered for the static condition was 7.658 and standard deviation 0.186.

![Figure 1: Mean speed limits](image)

<table>
<thead>
<tr>
<th>Table 1: Descriptive statistics of mean speeds</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
</tr>
<tr>
<td>-------</td>
</tr>
<tr>
<td>2-targets</td>
</tr>
<tr>
<td>4-targets</td>
</tr>
<tr>
<td>6-targets</td>
</tr>
<tr>
<td>x-targets</td>
</tr>
</tbody>
</table>

The elements of the correlation matrix \(C \in \mathbb{R}^{4 \times 4}\) of all initial data are shown in Table 2. The correlations are evaluated using correlation coefficient of Pearson-Brave.
Using principal component analysis for investigation

\[ r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \]  

(3)

where \( \bar{x}, \bar{y} \) - means of the both variables.

The matrix \( C \) gives the pair-wise correlations between all original variables. It is symmetric and all coefficients are positive. The respective significance levels are \( \text{Sig}=0.000<0.05 \) allowing to be considered in the analysis. The correlations between the 2-targets variable with the rest of the cases are moderate in the range [0.40-0.59], according the scale of Evans [19]. For the first three conditions, the strongest correlation is between the 4-targets and the 6-targets variables (0.736) and for the static variable (x-targets) - with the 4-targets variable (0.620).

Table 2: Correlation matrix of the variables

<table>
<thead>
<tr>
<th></th>
<th>2-targets</th>
<th>4-targets</th>
<th>6-targets</th>
<th>x-targets</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-targets</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4-targets</td>
<td>0.564</td>
<td>1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6-targets</td>
<td>0.466</td>
<td>0.736</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>x-targets</td>
<td>0.412</td>
<td>0.620</td>
<td>0.557</td>
<td>1</td>
</tr>
</tbody>
</table>

Before applying PCA several tests have been performed, as follows. First of all, there are not any unique variables and error variances in the current experiment. The variable correlations are neither below 0.1 nor above 0.9. Moreover, Kaiser-Meyer-Olkin’s (KMO) test can be calculated for multiple and individually variables. The overall KMO obtained on the data set is 0.779, which is the measure of the sampling adequacy. It is calculated using the values of the correlation coefficients between the variables in matrix \( C \) and those of the partial correlation coefficients, found on the main diagonal for each variable of the anti-image correlation matrix provided in SPSS (Table 3). The partial correlations measure the relationship between every two variables by removing the effect of the remaining variables. The overall KMO value fulfills the condition of being bigger than 0.5 and it is also close enough to 1, which is considered to be better for the analysis. The KMO for the individual variables are produced on the diagonal of the anti-image correlation matrix. The values should be above 0.5 for all variables and that condition is satisfied.

Table 3: Anti-image matrix

<table>
<thead>
<tr>
<th></th>
<th>2-targets</th>
<th>4-targets</th>
<th>6-targets</th>
<th>x-targets</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-targets</td>
<td>0.859</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4-targets</td>
<td>-0.322</td>
<td>0.712</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6-targets</td>
<td>-0.074</td>
<td>-0.542</td>
<td>0.763</td>
<td></td>
</tr>
<tr>
<td>x-targets</td>
<td>-0.080</td>
<td>-0.328</td>
<td>-0.182</td>
<td>0.855</td>
</tr>
</tbody>
</table>
Finally, a Bartlett’s test of sphericity has also been performed. The null hypothesis \( H_0 \), that the correlation matrix is an identity matrix has been tested and it has been rejected at a level of significance 0.05 (Sig=0.000<0.05). This means that the cloud of data has some sphericity. The Bartlett’s test indicates the extent of deviation from the reference situation \(|C|=1\). The small value \(|C|=0.183\) shows that the variables are highly correlated (under \( H_0 \), \(|C|=1\)).

All variables are standardized to z-scores beforehand. Following the above tests, the PCA can be performed efficiently.

Applying the PCA, the proportions of each variable's variance (Table 4), the accumulated variations and total variation (Table 5) in the data components are calculated. The communality value for each variable shows the part of the variable variance which can be explained by the principal components, i.e. the correlations between the variable and the component. The initial value of the communality in PCA is 1.

Table 4: Communalities

<table>
<thead>
<tr>
<th></th>
<th>Initial</th>
<th>Extraction ( h_i^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-targets</td>
<td>1.000</td>
<td>0.972</td>
</tr>
<tr>
<td>4-targets</td>
<td>1.000</td>
<td>0.817</td>
</tr>
<tr>
<td>6-targets</td>
<td>1.000</td>
<td>0.758</td>
</tr>
<tr>
<td>x-targets</td>
<td>1.000</td>
<td>0.751</td>
</tr>
</tbody>
</table>

In Table 5, the eigenvalues and the percentage of variance are shown. Four components corresponding to the number of variables in the experiment were determined by PCA. The absolute values of the eigenvalues or the amount of variance in the original variables accounted for by each component, were calculated and ordered from the largest to the smallest in the total column on the left part of the table: \( \lambda_1 = 2.692, \lambda_2 = 0.607, \lambda_3 = 0.456, \lambda_4 = 0.245 \). The total variance is equal to the number of variables used in the analysis, thus \( \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 = 4 \). The percentage of variance column gives the ratio, expressed as a percentage of the variance accounted for by each component to the total variance in all of the variables. The cumulative percentage column gives the percentage of variance accounted for by the four components.

Table 5: Total Variance Explained

<table>
<thead>
<tr>
<th>Components</th>
<th>Initial Eigenvalues</th>
<th>Extraction Sums of Squared Loadings</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Total</td>
<td>% of variance</td>
</tr>
<tr>
<td>1</td>
<td>2.692</td>
<td>67.304</td>
</tr>
<tr>
<td>2</td>
<td>0.607</td>
<td>15.171</td>
</tr>
<tr>
<td>3</td>
<td>0.456</td>
<td>11.394</td>
</tr>
<tr>
<td>4</td>
<td>0.245</td>
<td>6.132</td>
</tr>
</tbody>
</table>
According to Kaiser’s criterion, only the principal components with eigenvalues greater or equal to 1 should be considered in the analysis, because they account greater variation. In Table 5, only the first component satisfies this requirement \( \lambda_1 = 2.692 > 1 \).

The scree plot (Kettell’s criterion) graphs the eigenvalues against the component numbers and illustrates how components can be taken. Figure 2 shows that from the second eigenvalue, the curve starts becoming flat, making the first and the second components worth retaining.

A goodness-fit measure of informativeness which keeps enough components to account for 85\% of the variation is variance explained criterion. It is given by the ratio

\[
I_k = \frac{\lambda_1 + \lambda_2 + \ldots + \lambda_k}{\lambda_1 + \lambda_2 + \ldots + \lambda_m} \frac{\lambda_1 + \lambda_2 + \ldots + \lambda_k}{m}
\]

(4)

Using the eigenvalues from Table 5 and formula (4), the ratios are

\[
I_1 = 0.673, \ I_2 = 0.824, \ I_3 = 0.939, \ I_4 = 1
\]

On level of informativeness 0.85, the first two components are extracted. Based on these criteria, it was decided to retain the first two principal components which account together for 82.475\% of total variance and thus are considered important. The eigenvalues and the cumulative percentage in the extraction sums of squared loadings are shown in the right columns of Table 5. The first component of the initial solution is clearly much more important than the second.

The correlations between each observed variable and the respective component have been computed. These correlations are elements in the component matrix which has the following properties

\[
\sum_{j=1}^{k} a_{ij} = h_i, \ \ i = 1, m, \ \sum_{i=1}^{m} a_{ij}^2 = \lambda_j, \ j = 1, k
\]

(5)

All correlation values above 0.5 are considered to be important.

The initial (unrotated) solution plot of the component loadings and it is shown in Figure 3a. The first principal component is strongly correlated with all original variables and has maximum variance, thus it accounts for as much variation in the data as possible. It increases with increasing of all variable loadings. Moreover, the component correlates most strongly with the 4-targets variable, equal to 0.902.
The second principal component accounts for as much of the remaining variation as possible with the constraint that the correlation between the first and the second component is 0. It increases with only one of the variables, the 2-targets variable.

There is no clear separation of the variables in components. The component loadings of the 2-targets variable for the first principal component (0.728) and for the second principal component (0.665) have relatively close values. Thus, in order to clearly group this variable to one of the two principal components, a rotation is necessary. The idea is to redefine the component loadings to obtain optimal simple structure.

The reproduced correlation matrix (Table 6) shows the correlation based on the extracted components. The values on the diagonal are the same represented in the communalities table. It is considered ideal that the values in the reproduced matrix are as close as possible to the values in the original correlation matrix. The residuals (Table 6) represent the difference between the original correlations actually observed between the variables and the reproduced correlations. Most of the values are relatively small which shows that the two principal components solution provides a relatively good summary of the relationship in the data set.

<table>
<thead>
<tr>
<th>Reproduced correlation</th>
<th>2-targets</th>
<th>4-targets</th>
<th>6-targets</th>
<th>x-targets</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-targets</td>
<td>0.972</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4-targets</td>
<td>0.621</td>
<td>0.817</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6-targets</td>
<td>0.502</td>
<td>0.779</td>
<td>0.758</td>
<td></td>
</tr>
<tr>
<td>x-targets</td>
<td>0.334</td>
<td>0.731</td>
<td>0.736</td>
<td>0.751</td>
</tr>
<tr>
<td>Residual</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2-targets</td>
<td>-0.057</td>
<td>-0.036</td>
<td>-0.078</td>
<td></td>
</tr>
<tr>
<td>4-targets</td>
<td>-0.043</td>
<td>-0.111</td>
<td>-0.179</td>
<td></td>
</tr>
<tr>
<td>6-targets</td>
<td>-0.036</td>
<td>-0.043</td>
<td></td>
<td></td>
</tr>
<tr>
<td>x-targets</td>
<td>0.078</td>
<td>-0.111</td>
<td>-0.179</td>
<td></td>
</tr>
</tbody>
</table>
An oblique rotation (direct oblimin in SPSS) was selected as an initial rotation, assuming components are correlated. Since the correlations among components are 0.491>0.32 [24], then there is enough variance to guarantee oblique rotation. The rotation converged in 4 iterations. The oblique rotation delivered a pattern matrix (Table 7) which shows the component loadings for the rotated solution. The component loadings are similar to regression coefficients of the variable on each of the components and indicate the strength of the association between the variables and the components. The pattern matrix is suitable for the analysis since it provides a simple structure: each of the two components has variables with strong loadings and each variable loads strongly onto only one of the two components.

The 4-target, 6-target and x-targets variables have high positive loadings on the first principle component. However, the x-targets variable has the highest loading, equal to 0.927. The high mean set-size indicates a good VSTM. A high number of stationary objects correctly identified is predictive of a high number of moving 4 targets and 6 targets correctly identified. Thus, the first component is interpreted as “VSTM capacity”.

The 2-targets variable has a high positive loading on the second principle component only. This suggests that the mean speed is the highest for the 2 moving objects. However, the high speed for the identification of two objects is not a criterion for a good VSTM. Thus, the second component is considered as “Concentration”.

Table 7: Pattern matrix

<table>
<thead>
<tr>
<th></th>
<th>Component 1</th>
<th>Component 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>x-targets</td>
<td>0.927</td>
<td>-0.139</td>
</tr>
<tr>
<td>6-targets</td>
<td>0.827</td>
<td>0.082</td>
</tr>
<tr>
<td>4-targets</td>
<td>0.765</td>
<td>0.235</td>
</tr>
<tr>
<td>2-targets</td>
<td>0.033</td>
<td>0.970</td>
</tr>
</tbody>
</table>

The component plot of the rotated solution represents the component loadings, shown in Figure 3b. For the purpose of the component interpretation, it is considered to be better that the distribution of the points is closer to the axes and further from the origin. It implies that each variable has significant loading for one of the components and insignificant for the other.

In the right part of Table 8 are displayed the eigenvalues and percentage of variance explained for the two rotated components are displayed. The eigenvalues of the rotated component are 2.524 and 1.683, compared to 2.692 and 0.607 in the initial solution. The component scores can be considered to be variables describing how much every participant would score in a component. The scores are added to the initial data in SPSS.

They are standardized and are the result of the application of the rotated component loadings to the standardized scores of each participant on each the variables.
Table 8: Total Variance Explained after rotation

<table>
<thead>
<tr>
<th>Component</th>
<th>Initial Eigenvalues</th>
<th>Extraction Sums of Squared Loadings</th>
<th>Rotation Sums of Squared Loadings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>% of Variance</td>
<td>Cumulative %</td>
<td>Total</td>
</tr>
<tr>
<td>1</td>
<td>2.692</td>
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</tbody>
</table>

Table 9 shows the lowest and the highest values of the component scores between the 66 participants in the current experiment. This allows an assessment of each participant’s performance. For example, participant number 50 has the lowest standardized score in the first rotated component (-1.873) and therefore it can be said that the participant has low “VSTM capacity”. The same participant has a score close to average (-0.683) on “Concentration”. Participant number 1 has the highest standardized score in the first rotated component (2.477) and therefore it can be said that the participant has high “VSTM capacity”. The same participant has a high score (1.904) on “Concentration”.

Table 9: Participant scores on each principal component

<table>
<thead>
<tr>
<th></th>
<th>FAC_1</th>
<th>FAC_2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>2.477</td>
<td>1.904</td>
</tr>
<tr>
<td>40</td>
<td>-0.841</td>
<td>-2.465</td>
</tr>
<tr>
<td>50</td>
<td>-1.873</td>
<td>-0.683</td>
</tr>
<tr>
<td>66</td>
<td>2.335</td>
<td>2.081</td>
</tr>
</tbody>
</table>

The component scores can be treated as variables for further statistical analysis of variables. For instance, a t-test could be carried out to see if female or males have a better VSTM using the component scores for “VSTM capacity”.

5 Conclusion

Principle Component Analysis was applied to investigate the impact of mean speed and mean set-size in MOT in a psychological experiment and their correlation to VSTM and concentration. The analysis was done by extracting two
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principal components and by rotation with direct oblimin method in SPSS. The both components were interpreted as “VSTM capacity” and “Concentration”. The relative component scores allowed to measure how much every participant scored in each component.

The results showed a considerable effect of speed for tracking targets. The faster the speed was, the fewer targets were accurately tracked, and vice versa. Thus, the number of stationary targets remembered was higher than the number of targets correctly identified in the first three conditions. Hence, it suggests that the speed at which a participant can track a small number of objects is predictive of the number of stationary object locations he or she can memorize.

The mean speed was the highest for the 2 moving objects. However, it was not considered a criterion for a good VSTM, but for the level of concentration of the participants.

The mean set-size level instead was used as indicator of a good or bad VSTM. The number of objects tracked for static targets is predictive for the number of 4 and 6 moving objects tracked.

Moreover, the findings are consistent with Alvarez and Franconeri’s study (2007), which suggested a resource limit on tracking targets [3]. Thus, attempting to track a high number of objects at a high speed will lead to “scattering”, making objects impossible to track. The current PCA supported the flexibly allocated resource limit on tracking by extracting two components, which accounted for 82.475% of the variance in all conditions. Further research on the influence of speed and set-size in MOT can be done by involving more participants and differentiating them by age, sex, experience of objects tracking of the participants, etc. The principle component scores obtained can also be used for next statistical analysis.

References


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[27] L.M. Trick, D. Audet and L. Dales, Age differences in enumerating things that move: Implications for the development of multiple-object tracking,


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