Eye-Tracking in Practice: Results from a Study on Human Postures

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Abstract
In this article, we present preliminary results of a study that tries to determine where people are looking when ranking the stability of a model holding certain postures. A portable eye-tracker is used to record the original video data of people looking at human postures. Image processing is used to extract statistical information from the video data. Visualization and the Syrjala test are used for the statistical analyses.

Key Words: Eye-Tracking Data; Image Processing; Visualization; Software; `EyeTrackR` R Package; Syrjala Test

1. Introduction

An individual's planning and execution of actions is guided by many things, one of which is the anticipated posture at the end-state of an action. Studies on action planning indicate that future postural states can influence the choice of previous postures (Cohen and Rosenbaum, 2004; Herbort and Butz, 2010; Rosenbaum et al., 2006). For example, when grasping an overturned glass with the intent to pour water into it, the glass is typically grasped with a thumb-down posture so that the glass can be turned upward and the hand can end in a thumb-upward posture. This thumb-upward posture is also rated to be more comfortable than a thumb-down posture and is therefore one example of the end-state-comfort effect — the observed phenomenon whereby most actions end with a comfortable posture (Rosenbaum et al., 1990).

Our posture study aims to determine whether judgment of others' action capabilities is based on one's own action experiences. We examine the stability judgments of individuals viewing an actor holding different postures. Two groups of participants are examined: one group with extensive yoga experience and one group with minimal experience with actions that require stability (e.g., yoga, gymnastics, ballet dancing, etc.). We equip each participant from each group with mobile eye-tracking equipment that enables us to see what they are looking at as they make stability judgments. Moreover, the participants have to stand on a force plate and we measure their stability and balance during the experiment. We hypothesize that perceptions of others' stability will be influenced by the unique experiences of participants. More specifically, we hypothesize that those with extensive yoga experience will judge an actor to be more stable than those without stability-specific experience.

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Furthermore, we hypothesize that the visual information used to judge stability will differ between different groups of individuals with unique action experiences. Finally, the force plate measurements will allow us to assess whether participants who stand less stable will judge others to hold less stable postures as well.

This article is a continuation of our work originally presented in Symanzik et al. (2017). However, the previously described experimental design has been extended and modified. Data from the first five actual participants are available, rather than data from two test participants only. The primary goal of this article is to determine whether Syrjala's test (Syrjala, 1996), originally developed for spatial data, can be used for eye-tracking data. The Syrjala test is typically used to test for differences in the spatial distributions of two populations.

This article is structured as follows: In Section 2, we provide further details of our ongoing posture study. In Section 3, we introduce Syrjala's test and outline its original use for spatial data, followed by its application to our eye-tracking data in Section 4. All of our visualizations and analyses are conducted with the `R` statistical computing platform (R Core Team, 2018). In Section 5, we provide our conclusions and an outlook for the next steps in our ongoing posture study.

2. The Posture Study

"Does judging the action capabilities of another person depend on one's own experiences?" This is the primary research question for our planned posture study. For many human interactions, action anticipation must be present when interacting with others (e.g., to avoid collisions, pass something on to someone, etc.). This study is motivated by research conducted in the Kinesiology and Health Science Department at Utah State University (USU).

Most literature examining ones perceptions of others' action capabilities involves asking subjects to estimate the performance of another individual, e.g., "can Sally reach the block or not?" (Rochat, 1995). The visual information used by the participant in making their judgments has been limited to making a participant identify in what direction another person might be looking or what they might be looking at (Michelon and Zacks, 2006). We are unaware of any study looking at the use of eye-tracking to determine what particular visual information about an actor might be used for judgments about action capabilities. Therefore, no literature exists to describe how one might set up and conduct such a human posture study, in particular when incorporating mobile eye-tracking equipment as a major component of the data recording, data processing, and data analysis. Numerous preliminary test participants participated to help evaluate and refine the setup of the study. Data and results from two of these preliminary test participants were presented in Symanzik et al. (2017). Some extensions and modifications of the previously described experimental setup have been made based on feedback and the availability of additional hardware.

There are two groups of participants in our posture study. In Group 1, there are 20 students with minimal experience with actions that require stability (e.g., yoga, gymnastics, ballet dancing, etc.) from the undergraduate Psychology pool at USU. In Group 2, there are 20 students with extensive yoga experience from various yoga classes at USU. We anticipate that those with extensive yoga experience will judge an actor to be more stable than those without stability-specific experience. Moreover, we expect that the visual information used to judge stability will differ between different groups of individuals with unique action experiences.

Each of the 40 participants is shown 22 pictures of a single actor holding a posture. Twenty-two different postures were derived by systematically developing one posture per axis of rotation and within each axis of rotation, choosing three postures of increasing difficulty. Three postures were chosen for sagittal, frontal, and transverse plane rotation. Three postures were also chosen for the combination of sagittal and frontal, sagittal and transverse, frontal and transverse, and all three planes of rotation.[1] Therefore, 21 postures were developed with the addition of a posture with no rotation. The difficulty of the three postures within each rotation was arbitrarily determined by the experimenter. Figure 1 shows six of these postures.

All postures are shown to each participant in random order, projected to a wall, one at a time. Participants are required to judge the stability of each posture (i.e., how long the person could hold the posture) while standing on a force plate that measures their own movements and stability. Participants have to answer one single question for each of the postures: “How long could this person hold this posture?” Possible answers range from “1” to “6” where “1” relates to $\leq$ 1 sec, “2” relates to $>$ 1 sec – $\leq$ 10 sec, “3” relates to $>$ 10 sec – $\leq$ 1 min, “4” relates to $>$ 1 min – $\leq$ 10 min, “5” relates to $>$ 10 min – $\leq$ 1 h, and “6” relates to $>$ 1 h – $\leq$ 10 h. Figure 2 shows Posture 1 and the information shown to the participants. The other 21 postures are presented to the participants in a similar way.

The participants wear a mobile eye-tracking device from Applied Science Laboratories (ASL), Bedford, MA, for the entire study. This device uses one camera that continuously records the (changing) scene that is visible for the participant at a frequency of 30 Hz. Moreover, the focal point of the right eye is recorded by a second camera of this device and is overlaid as a cross-hair on each video frame of the recorded scene video. Details on these eye-tracker video recordings and how to extract the focal point of the eye in each video frame and translate it to the coordinates of a static image of the posture via the `EyeTrackR` R package can be found in Li and Symanzik (2016, 2017) and Li (2017).

The participants stand on a force plate, also called a force platform, during the entire experiment. A force plate measures the forces and moments that are applied to its surface as a subject stands or makes other movements on it. Force plates are used in scientific studies that are looking at balance (Karlsson and Frykberg, 2000) and sports performance (McNair and Prapavessis, 1999). The entire setup of the experiment is shown in Figure 3.

In practice, a static eye-tracker could be used as well for the eye-tracking posture study. However, we decided to use the mobile eye-tracker from ASL for three reasons. First, and most importantly, Fawcett (2016) reported that the static eye-tracker available at USU is not very precise for some areas of the computer screen. Thus, fixations from the posture study may not be matched with the proper body parts. Second, the posture study likely is a precursory step to future, more complex studies that will require the participants to do some physical movements in combination with recording the eye movements, e.g., where does a participant look when picking up an item. Such studies can’t be conducted with a static eye-tracker and a mobile eye-tracker must be used instead. Therefore, gaining some practical insights from a simpler experiment (such as the posture study) may be valuable for more complex future studies. Third, using the force plate in combination with a static eye-tracker where the participants are seated in front of a computer screen would not have been feasible.

The data obtained from the eye-tracker allow us to answer several secondary research questions: At which body parts (such as head, shoulders, hands, elbows, hips, knees, and feet) do the participants look for each posture? In the context of eye-tracking, these body parts are the areas of interest (AOIs) in each posture and have to be specified once for each posture, using the `EyeTrackR` R package. How long and how often do the participants look at the body parts in each posture? Are the viewing patterns of the participants associated with the stability assessment? Do the stability measurements from the partici-

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[1] The sagittal plane divides the human body into left and right halves, the frontal plane into front and back halves, and the transverse plane into superior and inferior halves.

Figure 1: Postures 1 to 6 (out of 22) used in the study.

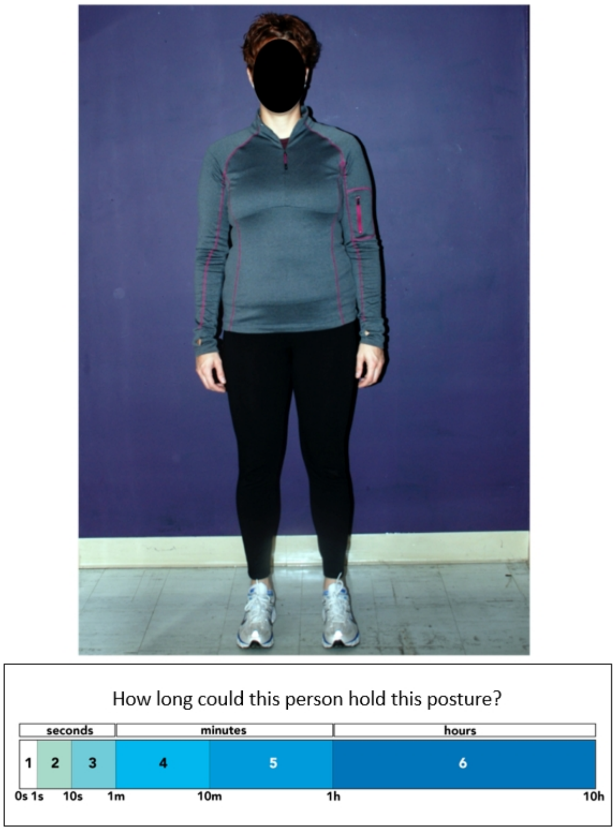

Figure 2: Posture 1 used in the study, the common question asked for each posture, and possible answer choices presented to the participants.

Figure 3: Setup of the experiment: Shown is one participant wearing the eye-tracking device and standing on the force plate while looking at a posture projected onto the wall.

pants relate to the stability assessments of the postures, i.e., do participants who have a less stable pattern indicate that the postures are also less stable, compared to participants who have a more stable pattern? Methods from machine learning may be used to answer these questions.

The data collection, when completed, will consist of 880 answers to the stability assessment (22 postures × 20 participants × 2 groups), 40 recordings, i.e., videos, from the eye-tracker (one for each participant), and 40 recordings from the force plate (one for each participant).

3. The Syrjala Test

The Syrjala test (Syrjala, 1996) is used to test for differences in the spatial distributions of two populations. The set of hypotheses associated with this test are:

H_0 : The normalized distributions of the populations are equal across the study area.

H_A : There is some unspecified difference in the normalized population distributions.

The test requires that both groups of interest are sampled at identical, pre-defined locations (x_k, y_k), $k = 1, \ldots, K$, across the study area $\mathcal{R}$. These non-negative coordinates are defined relative to their position within the bounding rectangle $\mathcal{A}$, with one of the corners of $\mathcal{A}$ defined as the origin. Note that this test is different from traditional tests of spatial point patterns. As stated in Syrjala (1996): "The random variable in this case is the observed density at the sampling location, not the location itself."

We now summarize the development of the Syrjala test: Using the original notation (Syrjala, 1996), let $d_t(x_k, y_k)$ denote the sample density of group t, $t = 1, 2$, at locations (x_k, y_k), $k = 1, \ldots, K$. Define $\gamma_t(x_k, y_k) = \frac{d_t(x_k, y_k)}{D_t}$ where $D_t = \sum_{k=1}^{K} d(x_k, y_k)$. This normalization of $d(x_k, y_k)$ ensures that the Syrjala test focuses only on differences in the spatial *distribution*, rather than in the spatial *abundance*. Finally, let $\Gamma_t(x, y) = \sum_{x_k \le x, y_k \le y} \gamma_t(x_k, y_k)$, which is the bivariate generalization of an empirical cumulative distribution function. Using these variable definitions, the Syrjala test statistic is defined as

$$\Psi = \sum_{k=1}^{K} \left[\Gamma_1(x_k, y_k) - \Gamma_2(x_k, y_k)\right]^2 . \tag{1}$$

Because this construction uses points near the origin more often than points in the center, a common adjustment to Syrjala's test is

$$\Psi = \frac{1}{4}\sum_{c=1}^{4}\Psi_c, \text{ where } \Psi_c = \sum_{k=1}^{K}\left[\Gamma_1(x_{c,k}, y_{c,k}) - \Gamma_2(x_{c,k}, y_{c,k})\right]^2 \tag{2}$$

and $(x_{c,k}, y_{c,k})$ are positive coordinates defined relative to each of the four corners of $\mathcal{A}$.

The Syrjala test is a bivariate extension of the Cramér-von Mises test (see Conover, 1998, Chapter 6, for a summary). Both tests compare the observed statistic to the set of all possible realizations of the statistic obtained through permutations of the values between groups. For the Syrjala test, let Ψ_n represent the $n = 1, \ldots, N$ possible permutations of Ψ. These permutations are formed by choosing to leave or swap the values of γ_1 and γ_2 at each sample location. This results in $N = 2^K$ possible scenarios for Ψ_n. Because these permutations obscure any true differences that might exist between the spatial distributions of the two groups, the comparison of Ψ to Ψ_n provides a measure of probability that the observed value of Ψ was simply due to random chance. The significance of the test is measured as

$$p = \frac{\sum_n I(\Psi_n \geq \Psi)}{N}, \tag{3}$$

where I represents the indicator function. This permutation based strategy requires no distributional assumptions. Since using all 2^K permutations is often computationally infeasible, the test is typically conducted using $N' \approx 1000 << N$ randomly selected permutations.

The Syrjala test has been applied to many different topics, most commonly in wildlife survey sampling. Examples of its use include 1) tests of differences in the spatial distributions of adult vs juvenile Pacific cod off the coast of Alaska (Syrjala, 1996), 2) tests of differences in the distribution of the same bird species over three consecutive years in Central Spain (Rey Benayas et al., 2010), and 3) tests of differences in the distribution of two different respiratory infections affecting turtles in the Mojave Desert (Berry et al., 2015). However, the Syrjala test has rarely been applied to eye-tracking research, with Chetverikov et al. (2018) as one of the few uses so far.

The following section discusses our application of Syrjala's test to visual gaze patterns obtained from the USU posture study that was introduced in the previous section.

4. The Syrjala Test and Eye-Tracking

In the eye-tracking literature, we make use of the terms fixations and saccades. A fixation refers to the state when the eye remains stable for a (short) period of time, and a saccade indicates rapid movement of the eye between two fixations.

Theoretically, eight possible combinations of the stability assessment of a posture, the fixations, and the saccades exist when comparing the answers of two participants:

(i) identical assessments, similar fixations, similar saccades

(ii) identical assessments, similar fixations, different saccades

(iii) identical assessments, different fixations, similar saccades

(iv) identical assessments, different fixations, different saccades

(v) different assessments, similar fixations, similar saccades

(vi) different assessments, similar fixations, different saccades

(vii) different assessments, different fixations, similar saccades

(viii) different assessments, different fixations, different saccades

In Symanzik et al. (2017), we visually assessed the viewing patterns for pairs of participants and reported our observations such as “identical assessments, similar fixations, similar saccades” or “different assessments, different fixations, different saccades”. In the following, we will use the Syrjala test to assess the similarities of the fixations for pairs of participants.

Figures 4 and 5 show scatterplots of viewing patterns for pairs of participants viewing four different postures. These graphs were produced with the *EyeTrackR* R package, described in Li and Symanzik (2016, 2017) and Li (2017).

In Figure 4, Posture (A), both participants focus on the upper body, starting at the chest and up to the head. The participant on the left also looks at the waist and stomach area and the right hand of the person in this posture.

In Figure 4, Posture (B), both participants focus on the upper body, in particular the stretched arms of the person in this posture. Both participants take a short glance at the waist and calfes.

In Figure 5, Posture (C), the participant on the left focuses on the body parts from the

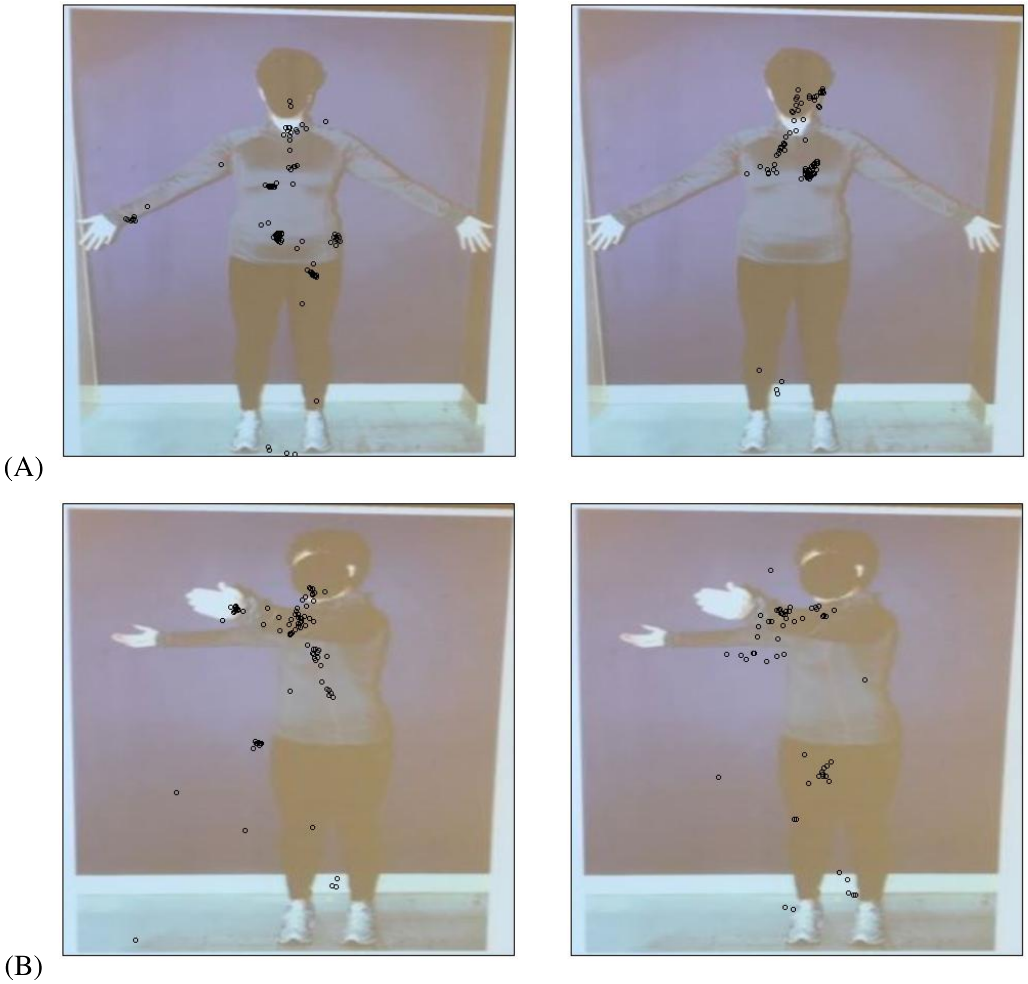

Figure 4: Scatterplots of viewing patterns of Postures A and B for pairs of participants.

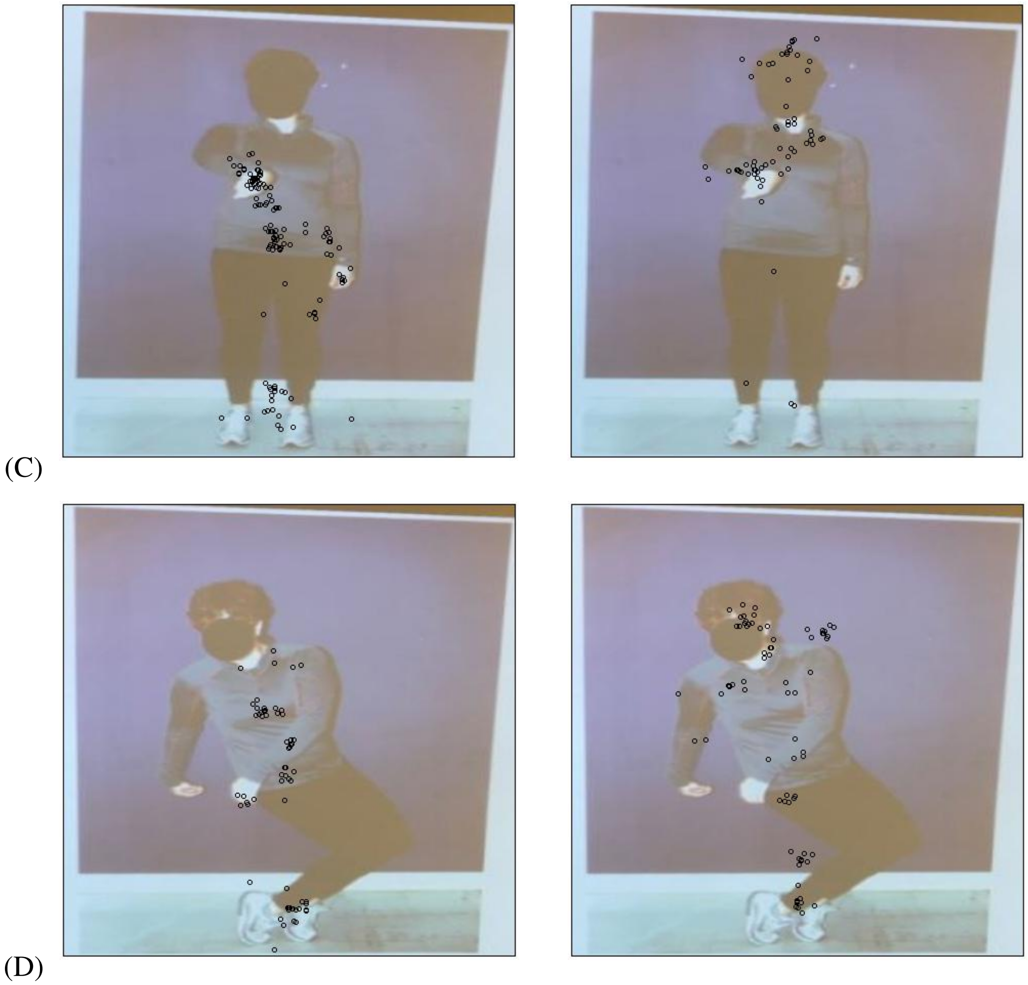

Figure 5: Scatterplots of viewing patterns of Postures C and D for pairs of participants.

arm that is held in front of the body down to the feet whereas the participant on the right focuses on the body parts from the arm that is held in front of the body up to the top of the head.

In Figure 5, Posture (D), both participants focus on the central body and ankles. The participant on the right also looks at the left shoulder and head of the person in this posture.

Our main interest for applying Syrjala's test is in determining if two fixation distributions are the same. However, recall that Syrjala's test requires that the two groups of interest are sampled at identical, pre-defined locations. Hence, the fixation points must be gathered into densities at sample locations. Two different data conversion techniques are employed. First, we define a regular grid across the posture regions, counting the number of fixations in each bin. The sample location is defined as the coordinates of the centroid of each grid. This is repeated across a 5×5, 10×10, and 20×20 grid (i.e., grids of 25, 100, and 400 bins). Second, we define a random set of sample locations (using a simple sequential inhibition process) across the posture regions, and assign each fixation point to the closest sample location (using Euclidean distance). This is also repeated for 25, 100, and 400 random points with minimum distances of at least 1/25 = 0.04, 1/100 = 0.01, and 1/400 = 0.0025, respectively.

Table 1 shows the results of Syrjala's test for Postures (A) through (D) for the six dif-

Table 1: Syrjala's test results for Postures (A) through (D). Statistically significant differences in viewing patterns ($p \leq 0.05$) are shown **in bold**. P-values tend to get smaller as the number of grid cells / random points increases, but this is not monotonic.

	Type of Data Conversion					
	Grid			Random Points		
Posture	5 × 5	10 × 10	20 × 20	25	100	400
A	0.279	0.057	**0.008**	0.164	0.066	**0.013**
B	0.618	0.554	0.310	0.758	0.418	0.334
C	**0.015**	**0.001**	**0.001**	**0.009**	**0.002**	**0.001**
D	0.238	0.109	**0.018**	0.170	0.095	**0.042**

ferent types of data conversion described above. These results highly depend on the type of data conversion (grid vs. random points) and the number of grid cells or random points, respectively. For Posture (B), none of the six test results are significant at the 5% significance level. For Posture (C), all of the six test results are significant at the 5% significance level. This matches with our visual assessment of these two viewing patterns. For Postures (A) and (D), two of the six test results are significant at the 5% significance level, all for the largest number of grid cells (20 × 20) and largest number of random points (400).

In addition to these four postures that are highlighted in detail in this article, we did a systematic comparison of all postures and test images for the five participants so far. Overall, a total of 144 tests [= (22 postures + 2 test images) × 6 data conversions] was conducted for each pair of participants: The minimum number of significant test outcomes was 8 ($\approx$ 6%) for one pair of participants. This could be due to chance, implying that those two participants had almost identical viewing patterns of the 22 postures (+ 2 test images). The maximum number of significant test outcomes was 43 ($\approx$ 30%) for a different pair of participants. This is no longer explainable by chance, implying that those two participants had rather different viewing patterns of the 22 postures (+ 2 test images). No big surprise, this largest difference occurred between one participant from Group 1 (with minimal experience with actions that require stability) and one participant from Group 2 (with extensive yoga experience).

5. Conclusions and Outlook

In this article, we used Syrjala's test to determine whether there are differences in the viewing patterns of pairs of participants who are looking at multiple postures. While the test results seem to match human judgments of which viewing patterns are similar and which are different, it should be noted that the results depend on the number of grid cells and random points used in the Syrjala test. Overall, there is a trend that the p-values of the test outcomes tend to get smaller as the number of grid cells / random points increases. Therefore, a single Syrjala test for a pair of participants does not seem to be meaningful. Running multiple versions of Syrjala tests and then combining the results seems to be more promising.

The literature offers several options how to combine multiple p-values, e.g., as $\sum \log p_i$ (Fisher, 1934), $-\sum \log(1 - p_i)$ (Pearson, 1933), $\sum p_i$ (Edgington, 1972), or $\min\{p_i\}$ (Tippett, 1931). Then, one could define cutoffs for these aggregated p-values to classify viewing patterns as *similar*, *somewhat different*, and *considerably different*. It might also be possible to further use these aggregated p-values (or a simple count of the number of the significant test results) for multidimensional scaling (Kruskal, 1964a,b).

Variants of the basic Syrjala test also exist and deserve some further investigation, such as the use of trajectories instead of fixed or random points (McAdam et al., 2012). Other alternative options to compare viewing patterns, e.g., the Jaccard index (Jaccard, 1912), could be applied to the areas of interest in each posture. It is important to keep in mind that we want to determine the similarity of the viewing patterns for participants from two groups and we do not have to come to a yes / no decision here.

The data collection process is ongoing and we expect it to be finalized by the end of the Fall 2018 semester. Further results will be reported thereafter.

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