Journal of Biomechanics 48 (2015) 1105–1111

Contents lists available at ScienceDirect

Journal of Biomechanics

journal homepage: www.elsevier.com/locate/jbiomech
www.JBiomech.com

Using mutual information to capture major concerns of postural control in a tossing activity

Harshvardhan Gazula [a,*], Chien-Chi Chang [b], Ming-Lun Lu [c], Simon M. Hsiang [a]

[a] Department of Industrial Engineering, Texas Tech University, Lubbock, TX 79409, USA
[b] Department of Industrial Engineering & Engineering Management, National Tsing Hua University, Taiwan, ROC
[c] National Institute for Occupational Safety and Health, 4676 Columbia Parkway, Cincinnati, OH 45226, USA

ARTICLE INFO

Article history:
Accepted 18 January 2015

Keywords:
Tossing
Information theory
Chow–Liu tree

ABSTRACT

Human body motion for load-tossing activity was partitioned into three phases using four critical events based on the load position viz. lift-off, closest to body, peak and release. For each phase, three objective functions values, viz. mobilization, stabilization and muscular torque utilization, used to control the motion patterns, were then calculated. We hypothesize that the relationships between different objective functions can be extracted using information theory. The kinematic data obtained with 36 treatment combinations (2 tossing distances, 2 tossing heights, 3 weights, and 3 target clearances) was used to estimate the mutual information between each pair of objective functions and construct Chow–Liu trees. Results from this research indicate that there was no dominant concern in the first two phases of the activity; however, torque utilization and mobilization were found to be important factors in the third phase of the load tossing activity.

1. Introduction

Manual material handling (MMH) tasks often involve various forms of body motion including lifting, carrying, pushing and pulling. One work physical activity that was often overlooked is tossing which constitutes 26% of all the MMH activities in industry (Delisle and Gagnon, 1995), possibly owing to its similarity with lifting. Tossing is especially a concern in garbage collection, construction, and baggage handling operations at airports, though little research is available in the literature for addressing the effects of tossing on body biomechanics and related injuries.

For prevention of musculoskeletal disorders, researchers have been employing various biomechanical modeling approaches to estimate joint loads and moments, particularly on the lumbar–sacrum region. The traditional biomechanical modeling approach, however, is limited to many uncertain properties of the human biological system. Many assumptions must be made to satisfy the biomechanical equilibrium such as kinematic redundancy (Ivaldi et al., 1988). Optimization is a common technique to satisfy this equilibrium. For example, Muth et al. (1978) derived an optimization model for assessing sagittal lifting. Chang et al. (2001) used a spacetime optimization approach to simulate lifting motion patterns. These techniques, however, face many obstacles such as presence of large uncertainties and search space leaving the system optimizer with a very large number of parameter combinations that are often infeasible to enumerate or simulate. Furthermore, because of the inherent complexity, non-linearity and over-redundancy in biological systems (Winter, 1985), it becomes difficult to capture the inter-relationships between different constraints over space and time using optimization techniques (Shan et al., 2004).

In this study, we used a different research approach to analyze the biomechanics of tossing. An optimal toss is characterized by a series of decisions so that the objective functions are optimized (e.g., minimized spinal loading and maximized accuracy of tossing). This is accomplished by a series of postural sequences over time. The sequence can only be understood in the context of other strategies that come before or after each strategy (carry-on effect) (Brehmer, 1992). Payne et al. (1988) showed that individuals use a variety of choice strategies for the same physical behavior. The selection of a strategy involves a trade-off between accuracy (good performance) and informativeness (reduction in uncertainty) (Yaniv and Foster, 1995). This research approach raises the challenge of humans' ability to utilize relevant information so as to be able to choose strategies for optimal body biomechanics. One solution to this challenge is the use of a structured relationship (Cooper and Herskovits, 1992) between different objective functions.

The amount of uncertainty about any behavior, including tossing, can be explained by a tree structure (Nielsen et al., 2008). That

* Corresponding author.
E-mail address: harshvardhan.gazula@ttu.edu (H. Gazula).

http://dx.doi.org/10.1016/j.jbiomech.2015.01.022
0021-9290/

is, the relationship among multiple objective functions when accounted for can lead to a great explanation/control over the tossing behavior. The aim of this study is to show the logical relationship between different objective functions, using mutual information (Cover et al., 1994), and to provide an overview of how those relationships change as the tossing task comes to a termination under different experimental conditions. Using information theory, it is possible to develop a series of trees/networks that capture uncertainty (and aid in the decision making/strategy selection process) during the various phases of tossing. The differences between these networks could be explained by changes in body biomechanics from phase to phase. When viewed in this manner, differences between networks/tree structures become interesting as they are a reflection how the information is flowing from phase to phase and this information flow helps us identify optimal tossing behavior.

2. Methods

2.1. Participants

Ten healthy college students (6 males and 4 females) free of injuries or history of musculoskeletal disorders and naive with actual MMH work participated in the study. The male and female subjects' mean (SD) ages were 29.0 (1.1) years and 23.8 (2.4) years; their statures were 169.0 (10.0) cm and 163.0 (2.0) cm; and their body weights were 75.0 (16.7) kg and 48.1 (4.0) kg, respectively. The study was carried out in the Ergonomics Laboratory of the Texas Tech University and the protocol was approved by the Institutional Review Board.

2.2. Experimental protocol

A $2 \times 2 \times 3 \times 3$ (distance—1 m, 1.5 m, height—floor, table (set to 53% of the subject's stature (waist height)), weight—1 kg, 5 kg, 7 kg, and target clearance—110%, 150%, 200%, respectively) factorial design was used in this study. Distance is defined as the distance between the subject and the target. Height is defined as the height at which the target is located. Weight is the weight of different loads used and target clearance is defined as the area of the target whose dimensions are *x*% times the dimensions of the load. Each subject was required to perform 10 trials for each condition. The subjects were required to take a mandatory rest for at least five minutes between changes in the treatment combinations, and allowed to rest between trials when they felt a need. To avoid fatigue during testing, nine test conditions were tested each day in a random order.

2.3. Experimental procedure

Test conditions were selected to mimic some typical MMH tossing tasks often observed in a warehouse. Prior to each trial, participants were instructed to stand at a prescribed start location. Participants picked a cardboard box ($30 \times 30 \times 20$ cm in size) of varying weights (of foam or bubble bag) from the ground and tossed it to the target location (on the ground or on to a table right in front of them) in one smooth motion. A landing plate was used to represent the target area.

2.4. Instrumentation

A six-camera Motion Analysis Falcon optical motion tracking system (Motion Analysis, USA) was used to capture subjects' motion during each trial. The kinematic data were collected at 60 Hz. Twelve 25-mm diameter retro-reflective markers on the main joints (wrist, elbow, shoulder, hip, knee and ankle) were affixed to each participant to track whole body motion. A combination of bony landmarks, measured anthropometry and marker positions was used to calculate each segment position. The center of mass (COM) position of each segment was calculated as a percentage of segment length from the proximal/distal end of the segment (Dempster, 1955). In addition, two markers were attached to the side of load which represented the shape and orientation of the load during the tossing task. An additional marker was attached to the side of the table which represented the center of the target location. Fig. 1 shows all marker positions.

2.5. Performance objectives

Hsiang and McGorry (1997) indexed and synthesized motion patterns of the external load by three biomechanically unique objective functions (concerns) viz., mobilization (M), stabilization (S) and strength utilization (T) and hence we use the same three objective functions in this study too. Mobilization is defined as a minimum jerk movement strategy (Flash and Hogan, 1985) and its mathematical expression is

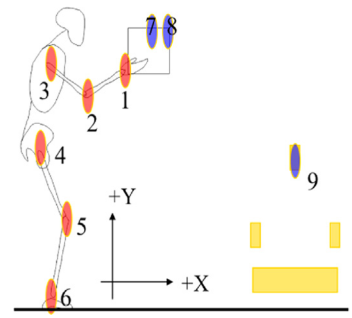

Fig. 1. Schematic diagram showing marker positions (1–wrist, 2—elbow, 3—shoulder, 4—hip, 5—knee, 6—ankle, 7—box left, 8—box right, and 9—target).

$$M = \left(\int_{t_i}^{t_f} \left[\frac{d^3X(t)}{dt^3}\right]^2 + \left[\frac{d^3Y(t)}{dt^3}\right]^2 dt \right) \tag{1}$$

where X and Y are horizontal and vertical positions of the hand:

$$X = \sum_{i=1}^{5} L_i \cos(\theta_i) \text{ and } Y = \sum_{i=1}^{5} L_i \sin(\theta_i)$$

(L_i is the length of segment i and θ_i is the angle made by joint i with the horizontal).

Stabilization minimizes any sudden or jerky change of the center of gravity of the body–load system and is given by

$$S = \left(\int_{t_i}^{t_f} \left[\frac{d^3X_{CG}(t)}{dt^3}\right]^2 + \left[\frac{d^3Y_{CG}(t)}{dt^3}\right]^2 dt \right) \tag{2}$$

where $X_{CG}(t)$ and $Y_{CG}(t)$ are the linear displacements of the center of gravity in the horizontal and the vertical directions of the body–load system, respectively.

The objective function of optimal strength utilization involves performance of the lift with the least possible effort from the five joints comprising the kinetic chain (Gagnon and Smyth, 1991). The mathematical expression is

$$T = \int_{t_i}^{t_f} \sum_{i=1}^{5} \left(\frac{M_i(t)}{S_i[\theta_i(t)]} \right)^2 dt \tag{3}$$

where S_j the moment strength of joint j and M_j is the reactive moment at joint j.

In all the above equations the limits of integration t_i and t_f are the times at which the tossing activity starts and finishes, respectively.

2.6. Phases in tossing and their identification

Since human physical and motor system has not developed to a stage where it can adapt to the changes in the task and environment instantly, human decision making process seldom arise instantly, rather they arise phase-wise (Meyer et al., 1988). To account for the delay in feedback, it makes it easier to think that the decision making happens in phases. A good coding system will capture the motion patterns and related postural control using the fewest necessary bits of information. Based on Occam's razor, Hsiang et al. (1998) demonstrated that the improvement of the resolution diminishes after the use of three phases separated by four events.

In the present study, each tossing task is divided into three phases marked by four events based on a coding system proposed by Hsiang et al. (1998). These four events were the initial position (lift off), the load closest-to-body-position, the highest position (peak), and the final position (release). Fig. 2 shows the body postures and load positions for the four events of a tossing task. Phase 1 is the period from lift-off to the load closest to body position. Phase 2 starts from the load closest-to-body position to the load being at the highest position. Phase 3 starts from this load at the highest position and to the release of the load.

All the tossing tasks were performed in the sagittal plane (XY in this case). Hence, the marker motion data from the right wrist (assuming symmetry) and the box was used to identify the four events described below.

1) Lift off: during lift off the wrist marker is at the lowest position (Y-direction).
2) Closest-to-body: this event is determined by identifying the point where the X position of the box marker or the wrist marker is at its lowest after lift off.
3) Peak: the highest point is identified as the peak position of the wrist marker before release.
4) Release: release is identified as the time instance when the difference in wrist to box distance at time t and $(t-1)$ is less than 0.5 cm.

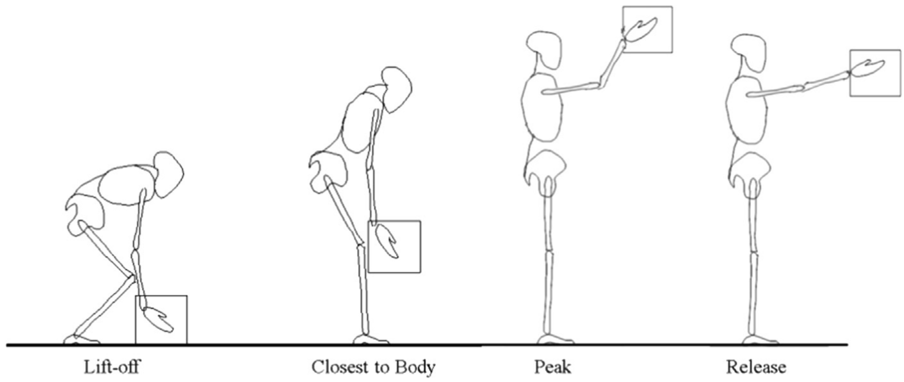

Fig. 2. Position of body and load during each event of a tossing task.

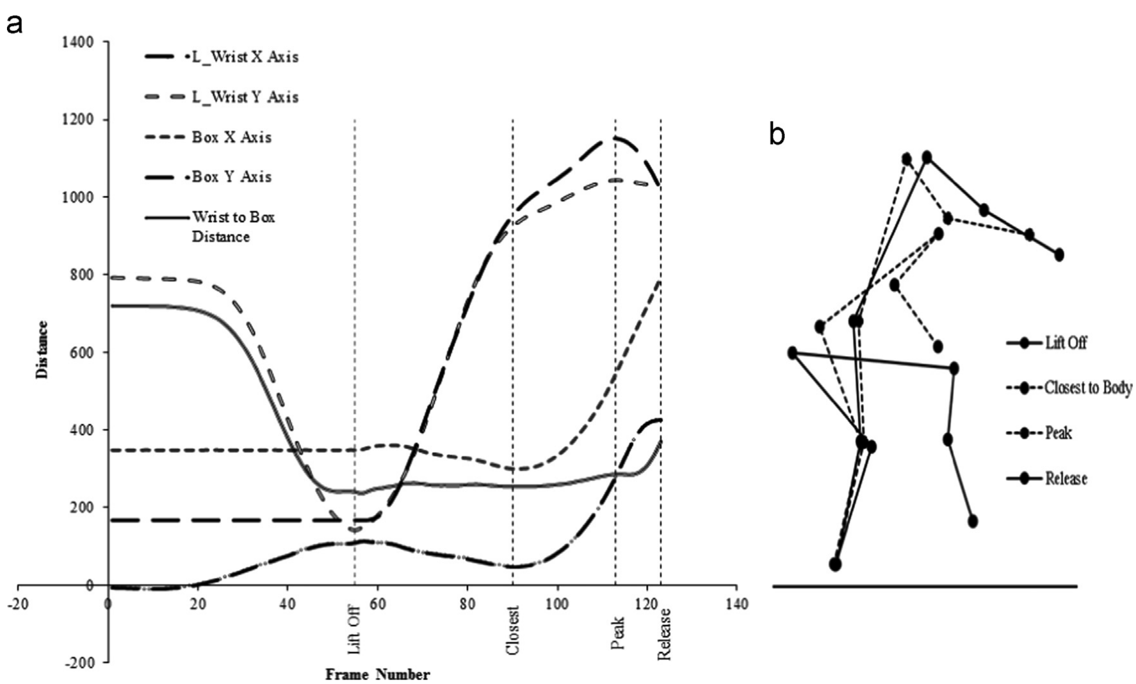

Fig. 3. (a) Plot showing identification of different phases of tossing and (b) combined graphic showing the body posture at each critical event from a sample motion capture data.

To illustrate the events and phases of the tossing tasks, a sample trial is used in Fig. 3. Fig. 3(a) shows the identification of the four events. Fig. 3(b) shows the schematic body position at each event.

2.7. Discretization

Once the phases in the tossing activity were delineated, we calculated the three objective function values for each phase as discussed in Hsiang and McGorry (1997). These three performance measures calculated for each subject across all trials lie on a continuous scale. To calculate mutual information we discretized the performance measures so as to build a conditional probability table (Fig. 4). The problem of variable discretization was essentially that of finding for each continuous variable X, a set of threshold values that partition the real line into a finite number of intervals. These intervals were the values of the discretized counterpart of X. We discretized each of the performance measures into three categories based on where they fell on the 33.33 (Lo-Low), 66.66 (Med-Medium) and 100 (Hi-High) percentiles scale to guarantee capturing the interaction with adjacent variables in the network. This discretization was performed separately for all phases.

2.8. Information theory and mutual information

Mutual information (MI) is a quantitative measurement of how much one random variable tells us about another random variable (Cover et al., 1994).

In this study, information was thought of as a reduction in the uncertainty of a variable. Thus, the more mutual information between S and M (I), the less uncertainty there is in S knowing M or M knowing S. In other words, MI is a measure of dependence of one objective function on another. The formula to calculate the MI between two random variables S and M is given as follows (Cover et al., 1994):

$$I(S;M) = \sum_{s \in S}\sum_{m \in M} p(s,m)\log\left(\frac{p(s,m)}{p(s)p(m)}\right),$$

where $p(s,m)$ is the joint probability distribution function of S and M, and $p(s)$ and $p(m)$ are the marginal probability distributions of S and M, respectively, all obtained from the conditional probability table.

2.9. Chow–Liu tree and its generation

Presumably, we have some idea about a feasible tossing trajectory (an output) that can be predicted by a certain set of inputs (e.g., joint angles). However, we do not understand how subjects' choice of inputs determines the output. Chow–Liu tree (Chow and Liu, 1968), a type of graphical probabilistic model, is the representing agency with the ability to decipher this underlying mechanism. The framework is graphical in that a graph composed of nodes and links represents the causal structure of a system, with nodes corresponding to variables in the causal system, and undirected links between nodes. It allows us to reason about events when we are unsure about what has happened, what will or would happen, and even about how events lead to one another. In other words, it is a greedy approach for uncertainty reduction. A Chow–Liu tree requires data to be discretized to form conditional probability tables which has been discussed earlier. The following

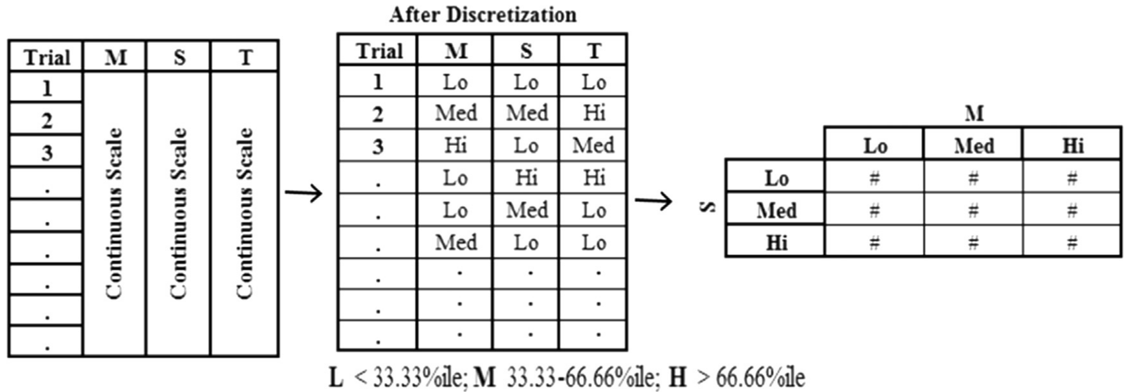

Fig. 4. Flow chart showing steps involved in developing a condition probability table.

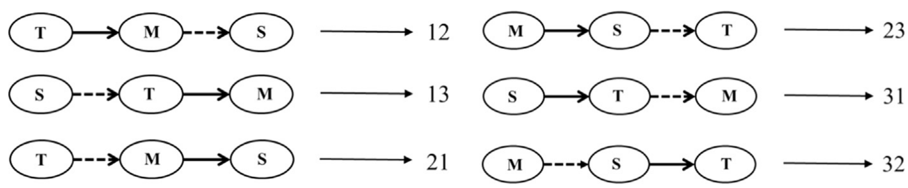

Fig. 5. Description of different Chow–Liu trees generated using three variables (T→M=1; M→S=2; S→T=3).

algorithm (Chow and Liu, 1968) lists out the steps involved in building a Chow–Liu tree using the MI of every pair of values.

1) Compute the MI of each possible pair of objective functions.
2) Find a maximum weight spanning tree.
   a. Sort the MI values of every pair in decreasing order.
   b. Pick the pair with the highest MI value.
   c. Make it the first two nodes with an edge added in between.
   d. Now pick the next best pair and repeat step (c).
   e. Greedily add edges; just make sure it is a tree at every step.
   f. We now, have a Chow–Liu tree.

Based on the algorithm described above, we first calculated the values of the three performance measures to develop such structural relationships between the performance measures under each experimental condition for each subject. Each structure was classified as 12/13/21/23/31/32 in (Fig. 5) on the basis of the pairs that have the first highest (solid edge) and second highest (broken edge) MI values. We built six different configurations of Chow–Liu trees.

3. Results and discussion

Results of the study are presented as the primary concerns (pair of objective functions with the highest MI value) among the previously considered objective functions in each phase of the tossing activity under different experimental conditions. Fig. 6 shows the percentage of subjects who exhibited each of the possible tree structures in each phase of the tossing task under different conditions. It can be seen that 70% of the subjects exhibited the tree structure 13 while tossing the loads on floor in Phase 3. While tossing the loads on table, 40% and 30% of the subjects exhibited the tree structures 12 and 13 in Phase 3, respectively. While tossing the loads to a distance of 1 m, 60% of the subjects exhibited the tree relationship 12 and 40% exhibited 13 in Phase 3. While tossing the loads in a distance of 1.5 m, 50% of the subjects exhibited the tree 13 in Phase 3. No dominant tree relationship was observed for Phases 1 and 2.

When tossing a 1 kg load in Phase 3, 60% of the subjects demonstrated the tree relationship 13, while 30% exhibited the tree relationship 12. However, when tossing a 5 kg load, the opposite was observed. While tossing a 7 kg load, 30% of the subjects exhibited the tree relationships 12 and 13. The results for tossing a 7 kg load were based on a subset of the data excluding 2 subjects that did not toss the 7 kg load owing to some technical problems.

When tossing the loads in each of the three clearance levels (110%, 150% and 200%), at least 50% of the subjects exhibited a tree structural relationship indicated by either 12 or 13. No clear patterns were found for Phases 1 and 2 for different load and clearance conditions. Loads are thought to have a significant impact on subjects' body kinematics when performing a tossing task.

In short, during Phase 3 of tossing, most subjects resorted to a type of tossing pattern that showed ‘Mobilization’ as the most important concern under almost all the experimental conditions. These findings suggest that mobilization is an important concern at the moment the load is released from the hand.

Fig. 7 shows the percentage of time for each of the tree structures exhibited by each subject under all the experimental conditions. A 50% of time was used as the criterion for selecting a major tree structure. In Phase 1, Subject 1 exhibited the major tree structure 12 (89% of the time), Subjects 2 and 6 had the major tree structure 13 (60% and 70% of the time, respectively). Subjects 3 and 7 had the tree 21 (60% and 50% of the time, respectively). Subjects 5 and 9 exhibited the major tree structures 23 and 31 (50% of the time). Subjects 4 and 8 did not have a clear time percentage pattern for the tree structures.

In Phase 2, none except Subjects 2, 3 and 6 had a clear major tree structure. It should be noted that almost all the subjects, except Subjects 8 and 9, exhibited the tree structures 12 and 13 for the majority of the times. Specifically, Subjects 3 and 5 exhibited the tree structure 12 for 70% and 50% of the time, respectively. Subjects 1, 2, 6, 7 and 10 exhibited the tree structure 13 for 55.55%, 80%, 70%, 60% and 66.6% of the time, respectively.

Generally, the subjects showed a motion pattern for the tossing tasks in Phases 1 and 3 but not in Phase 2. The tree structural relationships 12 and 13 exhibited by the majority of the subjects in Phase 3 of the tossing tasks were found in most test conditions. This common tree structure (12/13) may explain the importance of the torque and mobilization factors in determining the success of the tossing activity. This finding supports our prior observation that in the third phase of the tossing activity, motion behavior is dictated by ‘mobilization’ in addition to ‘torque utilization’.

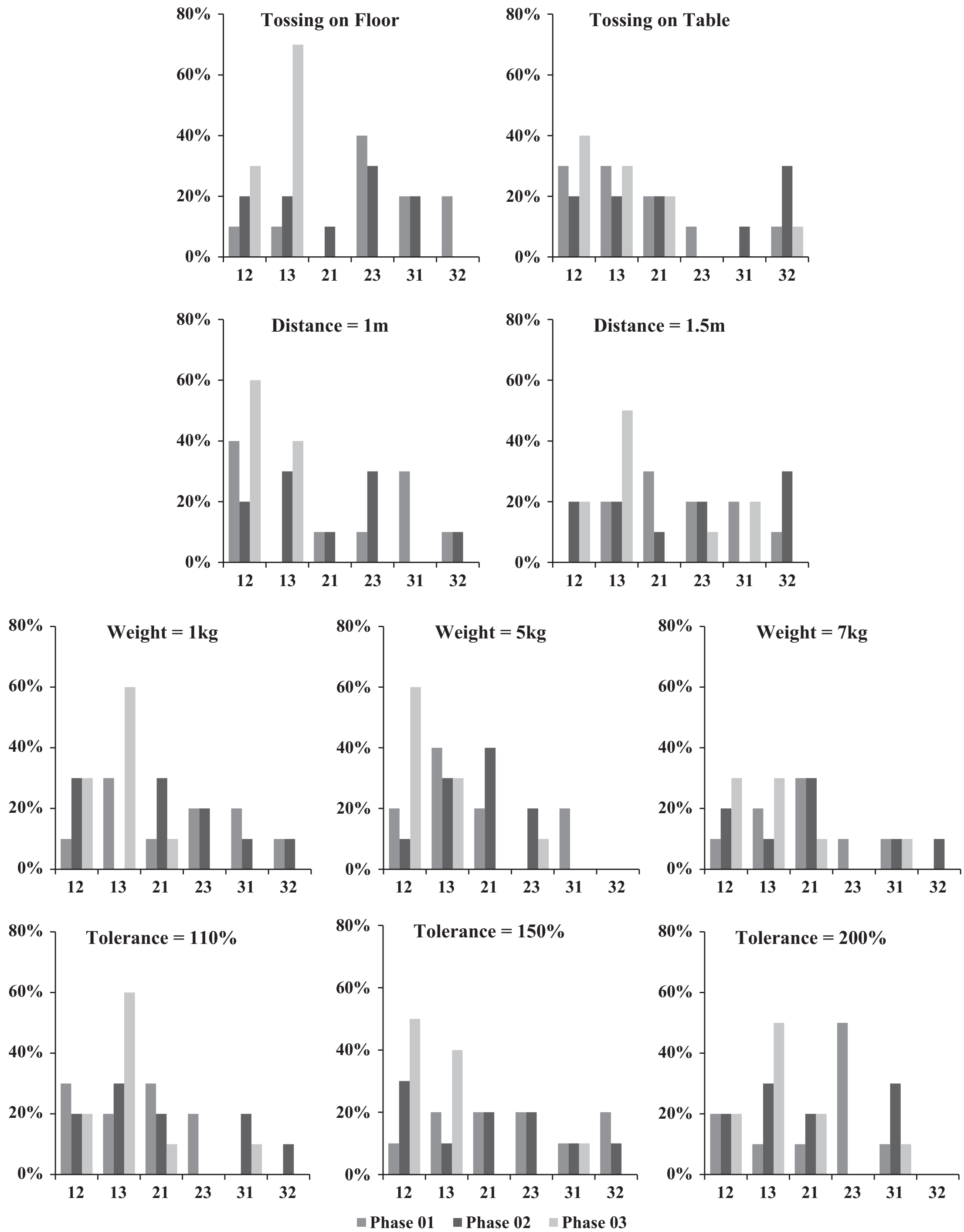

Fig. 6. Percentage of subjects exhibiting each tree structure in each phase (in each condition).

Once a database of the structural relationships between the objective functions, in each phase for different experimental conditions, has been established (based on data collected from a large population), it can be used as a decision-support tool. Two sample trees (01) and (02) shown in Fig. 8 will be used to explain how diagnosis can be done using such a tool. Let us assume that under similar conditions, two subjects 1 and 2 are observed to follow the behavior as described by tree 01 and tree 02, respectively. And, if we also know that under those conditions, tree 01 is the optimal behavior for best performance. By observation, we know that, subject 02 has a risk of injury potential in phase 1 and the ergonomist can recommend suitable changes to his task design or provide necessary intervention. However, identifying the influence of various constraints on the progress of the concerns and subsequent outcome of the activity is beyond the scope of this current work and we leave it for future study.

Some other limitations in the study are worthy of mentioning. The current work presents a methodology to identify the primary/secondary concerns (objective function pairs with the highest and second highest MI values) in each phase of a tossing activity and if these concerns remain the same throughout the activity or change as the activity progresses. Hence, ten subjects used in the present study may limit the interpretations of the study results. Additionally, results based on the limited test conditions cannot be generalized

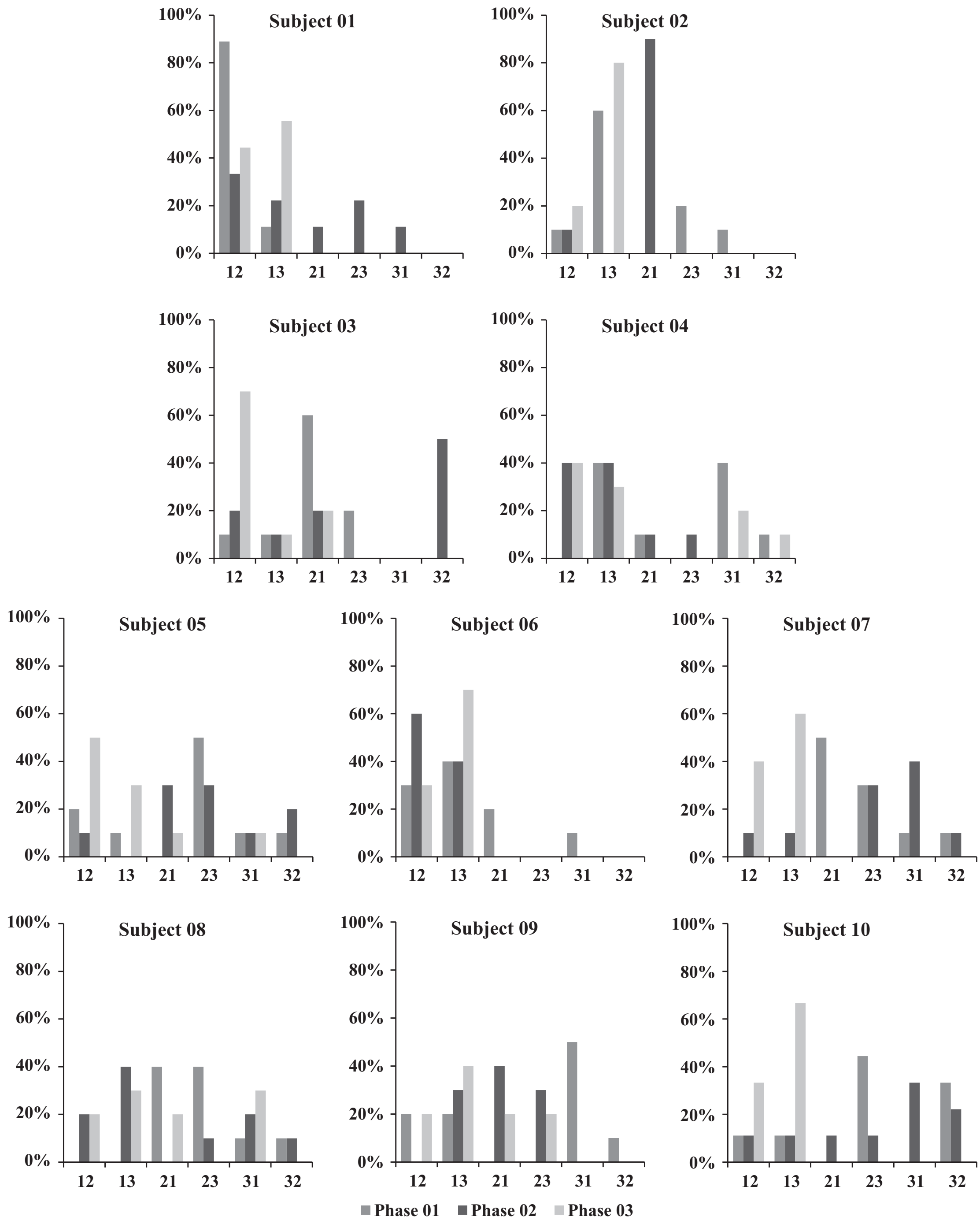

Fig. 7. Percentage of times a tree structure was exhibited in each phase (for each subject).

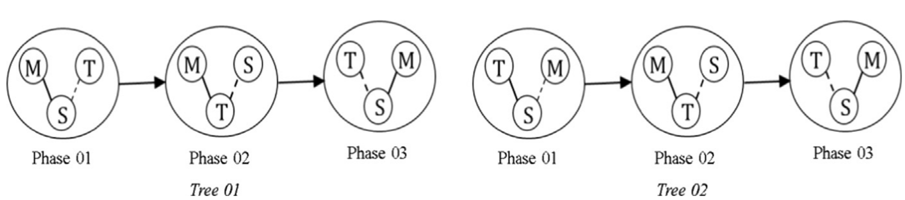

Fig. 8. Two example trees showing the objective functions relationships in each phase.

for other different tossing conditions, for example, underarm precision throwing (Dupuy et al., 2000) and overarm throwing (Stodden et al., 2006). The goal of this paper, however, is to demonstrate the usefulness of combining information theory and Chow–Liu probabilistic graphical model for identifying motion behavior patterns for tossing tasks. Most previous research on MMH focused on the peak or average values of the kinematic data over the course of a MMH task without considering the sequence of the phases of the kinematic data. Understanding the relationship between body kinematic characteristics between phases of a MMH task is of importance because motion is executed by a series of decisions to accomplish a motor task (Gahery and Massion, 1981). Although the study findings are based on a simpler 2D biomechanical model, it can be expanded to higher dimensions too. In addition, although only three objective functions have been used in this study, many more objective functions can be added without loss of generality.

The key is to identify information regarding systematic relations that hold between objective functions that concern behavior and use such information in determining the right input needed to lead to a desired outcome. We hypothesize that knowing the systematic relations between actions and their outcomes in terms of the major concerns, the right action can be chosen at the right time for an effective control (Sloman, 2009).

4. Conclusion

In this paper, we introduced a novel uncertainty reduction approach for the identification of body kinematic patterns and their logical organization based on different objective functions at different phases of a tossing task. The proposed research concept based on mutual information provides users with a useful diagnosis of the relevance of different objective functions and of the mutual dependencies in designing the task (Battiti, 1994). The broader impact of this work lies in the fact that this type of biomechanical data-mining approach possesses an important advantage over biomechanical optimization, where accurate physics-based dynamical/optimization models may be prohibitively complex. Future work includes extending the above work to three dimensional models and also to tossing activities where there are obstacles to the activity and where the activity is performed in the frontal plane (to the side). In addition this work is not just limited to tossing and can be extended to any manual material handling activity.

Conflict of interest statement

The findings and conclusions in this report are those of the authors and do not necessarily represent the views of the National Institute for Occupational Safety and Health. The authors also declare that they have no conflict of interest.

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