Điểm lại về các phương pháp nhận biết chuyển động người[[1]](#footnote-1)

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Nhận biết chuyển động người từ những hình ảnh hay những video liên tục là thách thức đối mặt với những vấn đề, như tách nền, thiếu bộ phận cục bộ(partial occlusion), thay đổi tỷ lệ, điểm nhìn, ánh sáng và sự khác biệt ngoại hình. Rất nhiều những ứng dụng, bao gồm các hệ thống theo dõi video, tương tác người máy, các máy móc mô tả hành vi con người, cần đến một hệ thống nhận biết chuyển động người. Trong bài viết này, chúng tôi sẽ kể ra một cách chi tiết những nghiên cứu tiến bộ nhất trong lĩnh vực nhận biết chuyển động người. Mong muốn sẽ đưa ra được một tập hợp các phương pháp nhận biết chuyển động người và thảo luận về ưu khuyết điểm của chúng. Cụ thể, chúng tôi sẽ chia các phương pháp phân lớp người thành 2 nhóm lớn dựa vào việc chúng có sử dụng dữ liệu từ các modal khác nhau hay không. Sau đó, mỗi nhóm sẽ được phân tích sâu hơn bằng cách chia thành các nhóm nhỏ hơn phân biệc bằng việc làm thế nào để các nhóm này mô hình hóa hoạt động của con người và loại hoạt động mà chúng quan tâm. Hơn nữa, chúng tôi cung cấp một phân tích toàn diện về những bộ dữ liệu đã công bố và khảo sát về những yêu cầu cần thiết của một bộ dữ liệu về hoạt động người. Cuối cùng, chúng tôi báo cáo về các đặc trung của các hướng nghiên cứu tương lai và đưa ra các vấn đề mở trong việc nhận biết chuyển động người. Thêm vào đó,

# Giới thiệu

Nhận biết hoạt động người là làm việc với một dấu hiệu rõ rệt trong tương tác người với người và tương tác cá nhân của người. Vì việc này cung cấp thông tin về con người, tính cách của họ, trạng thái tâm lý của họ và những thông tin này rất khó để trích xuất. Khả năng nhìn ra hành động của một người khác là một trong những chủ đề chính trong lĩnh vực nghiên cứu của thị giác máy tính và máy học. Kết quả của nghiên cứu này cho thấy rất nhiều ứng dụng bao gồm các hệ thống giám sát video, tương tác người máy, và khoa học người máy về các đặc điểm hành vi của con người cần đến một hệ thống nhận biết hành vi của con người.

Xét đến nhiều công nghệ phân lớp đã có thì ta thấy được rằng có 2 câu hỏi chính được đặt ra, một là: “Hành động nào?” (để phát hiện vấn đề) và hai là: “Hành động đó ở đâu trong video?” (để xác định vị trí của vấn đề). Trong khi cố gắng nhận biết hành động người, ta phải xác định các trạng thái chuyển động của người đó, đẻ máy tính có thể nhận biết một cách hiệu quả hành động của người đó là gì. Hành động của con người, như là “đi bộ” hay “chạy”, xuất hiện rất thường nhật trong đời sống của con người và khá dễ dàng để nhận ra. Bên cạnh đó, những hành động phức tạp hơn, như “gọt táo”, rất khó để nhận ra. Các hoạt động phức tạp có thể được chia nhỏ ra thành các hoạt động nhỏ hơn để có thể dễ dàng nhận biết. Thông thường, việc nhận ra một vật thể trong khung hình sẽ ta hiểu rõ hơn về hoạt động của người trong khung hình đó bằng cách cung cấp những thông tin hữu ích về các sự kiện đang diễn ra.

Hầu hết các công việc trong việc nhận biết chuyển động người là nhặt ra cảnh chính của khung hình, nơi mà diễn viên có thể tự do thể hiện hoạt động của mình. Sự phát triển của một hệ thống tự động nhận biết chuyển động người, khả năng phân lớp hành động người với độ lỗi thấp, là một thách thức lớn dựa trên các vấn đề, như tách lớp nền, khuất cục bộ, thay đổi tỉ lệ, thay đổi ánh sáng, diện mạo, và độ phân giải khung hình. Thêm vào đó, việc tính toán vai trò của hành vi tốn rất nhiều thời gian và cần một lượng tri thức rất lớn về các sự kiện đặc thù. Hơn thế nữa, các lớp trong và ngoài tương tự nhau khiến việc thực hiện càng thêm thách thức. Như là với những hành động cùng một lớp có thể được nhận biết khác nhau với những người có cách di chuyển khác nhau, và những hành động giữa 2 lớp khác nhau trở nên khó phân biệt khi chúng được thể hiện gần giống nhau. Cách mà con người thể hiện một hành động tùy thuộc vào tập quán hằng ngày của họ, và đó cũng là một thử thách lớn cho việc nhận biết. Mô phỏng hành động và phân tích chuyển động con người từ những bộ dữ liệu kém tiêu chuẩn cũng là một thử thách lớn không kém.

Để vượt qua hết tất cả những vấn đề này, ta có 3 phương pháp chính: (i) tách nền, (Elgammal et al., 2002; Mumtaz et al., 2014), là hệ thống phân tách các phần của ảnh không thay đổi theo thời gian (nền) ra khỏi các vật thể chuyển động và thay đổi; (ii) theo vết người (Liu et al., 2010; Wang et al., 2013; Yan et al., 2014), là hệ thống xác định vị trí của người theo thời gian; (iii) nhận diện chuyển động người và vật thể (Pirsiavash and Ramanan, 2012; Gan et al., 2015; Jainy et al., 2015), là hệ thống định vị các chuyển động trong ảnh.

Mục tiêu của nhận biết chuyển động người là quan sát các chuyển động trong các video liên tục hay ảnh. Vì thực tế này nên các hệ thống nhận biết chuyển động người hướng tới việc phân chia chính xác dữ liệu đầu vào vào các tập. Vì chuyển động người rất phức tạp nên chúng được chia thành: (i) cử chỉ; (ii) hoạt động nhỏ; (iii) Giao tiếp người-vật hoặc người-người; (iv) hoạt động nhóm; (v) hành vi; (vi) sự kiện.

Cử chỉ được xét như các chuyển động thô của các bộ phận cơ thể người có thể ứng với các hành động tiêu biểu của người đó. Hành động nhỏ là các chuyển động của người được miêu tả như một hành động có thể cấu thành những hành động phức tạp hơn. Giao tiếp người-vật hay người-người là các hoạt động của người với sự tham gia của từ 2 người (hoặc) vật trở lên.Hoạt động nhóm là hoạt động có sự tham gia của một nhóm người. Cuối cùng, sự kiện là những hoạt động cao cấp như hoạt động xã hội của con người.

Dàn ý của bài báo này được tổ chức như sau: phần 2 là một khảo sát ngắn về các nghiên cứu đã công bố; phần 3 giới thiệu các lóp hoạt động người; phần 4, 5 khảo sát các phương pháp nhận diện người và phân tích ưu khuyết điểm của từng nhóm; phần 6 đưa ra một tập hợp các bộ dữ liệu và thảo luận về các hướng nghiên cứu tương lail và cuối cùng phần 7 là kết luận.

# Các nghiên cứu trước đây và phân loại

Có rất nhiều nghiên cứu trong lĩnh vực nhận biết chuyển động người. Gavrila (1999) đã chia chúng ra thành 2 hướng tiếp cận là 2D (có hay không có mô hình hiện) và 3D. Aggarwal and Cai (1999) đưa ra một cách phân loại khác tập trung vào phân tích chuyển động người, theo vết từ camera đơn và đa cảnh, nhận biết chuyển động người. Cùng hướng với cách phân loại trên, Wang et al.(2003) hướng đến việc phân cấp các hành động người. Moeslund et al. (2006) tập trung

# CORTICAL PROCESSING OF CONTOURS

Visual information passes along the optic nerve from the retina of the eye where it is relayed, via a set of synaptic junctions in the midbrain lateral geniculate nucleus, to the primary visual cortex at the back or the brain (Visual Area 1 or V1). It has been known since the Hubel and Wiesel's work in the 60s that the visual cortex contains billions of neurons that are sensitive to oriented edges and contours in the light falling on the retina. Such neurons have localized receptive fields each responding to the orientation information contained within the light imaged in a small patch of retina. A widely used mathematical model of a V1 neuron's receptive field is the Gabor function [Daugman 1985]:

 (1)

Hubel and Wiesel [Hubel and Wiesel 1962, Hubel and Wiesel 1968] found that neurons responding to similar orientations were clustered together in a structure they called a column which extended from the surface of the visual cortex to the white matter (see Figure 1). Later, they and other researchers discovered hypercolumn structures consisting of thousands of neurons all responding to the same area of visual space and selecting for a range of orientations. Overall, V1 contains a topographic map of the visual field having the property that every part of the retinal image is processed in parallel for all orientations. These orientation selective neurons have provided the basis for all subsequent theories of contour and edge detection.



Fig. 1. Neurons are arranged in V1 in a column architecture. Neurons in a particular column respond preferentially to the same edge orientation. Moving across the cortex (by a minute amount) yields columns responding to edges having different orientations. A hypercolumn is a section of cortex that represents a complete set of orientations for a particular location in space.

There remains the problem of how the output of orientation sensitive neurons, each responding to different parts of a visual contour, becomes combined to represent the whole contour. Part of the solution appears to be a contour enhancement mechanism. [Field et al. 1993] examined the human's ability to perceive a contour composed of discrete oriented elements. They placed a contour composed of separated Gabor patches, among a field of randomly orientated Gabor patches. Contours were detected when the patches were smoothly aligned. They were not detected when there was misalignment. This work suggests that there is some manner of lateral coupling among the visual elements involved in perceiving the Gabor patches in the contour. These researchers have suggested that similarly oriented aligned contours mutually excite one another, while they inhibit other neurons that are nearby (Figure 2).



Fig. 2. Neurons whose receptive fields are aligned along a continuous contour mutually reinforce each other. They inhibit nearby neurons with a similar orientation sensitivity.

# LI'S V1 MODEL

Based on the observed organization of the neurons in the visual cortex by Hubel and Wiesel [Hubel and Wiesel 1962, Hubel and Wiesel 1968] and the experimental evidence by [Field et al. 1993], Zhaoping Li constructed a simplified model of the behavior of V1 neurons and examined the model's ability to integrate contours across multiple V1 neurons. The model is introduced briefly here, and described in more detail in [Li 1998]. In Li's model, the cortex is approximated by a set of hypercolumns arranged in a hexagonal grid. Each hexagonal cell has 12 orientation-selective neuron pairs oriented in 15-degree increments. One of the main simplifications embodied in Li's model is that it fails to incorporate the way the mammalian visual systems scales with respect to the fovea. Real neural architectures have much smaller receptive fields near the fovea at the center of vision than at the edges of the visual field. The neurons in each hex cell were grouped into excitatory and inhibitory pairs responding to an edge of a particular orientation at that location. Thus there were a total of 24 neurons per cell. The firing rates of both the inhibitory and excitatory neurons were modeled with real values. The neuron pairs affected neighboring neuron pairs via a transfer function that depended on the alignment of the edge selectivity orientations. Neuron pairs that were aligned with one another exhibited an excitatory effect on each other, while pairs that were not aligned inhibited each other. Finally, Li's model also contains feedback pathways for higher-level visual areas to influence individual neurons.

In our implementation, the mapping of the hexagonal grid to the image space was such that the hex centers were separated by 10 pixels. For the V1 neuron response, we used the Gabor function (Eq. (1)) with a wavelength, λ, of 21 pixels, a σ of 7 pixels, and an aspect ratio, γ, of 1.

# STREAMLINE TRACING ALGORITHM

[Laidlaw et al. 2001] compared the effectiveness of visualization techniques by presenting test subjects with the task of estimating where a particle placed in the center of a flow field would exit a circle. Six different flow-field visualization methods were assessed by comparing the difference between the actual exit numerically calculated and the estimation of the exit by the human subjects. Laidlaw et al.'s experiment was carried out on humans but, in our work, we apply this evaluation technique to humans as well as to our model of the human visual system and use a streamline tracing algorithm to trace the path of the particle.

We use the term streamline tracing to describe the higher level process that must exist for people to judge a streamline pathway. We call it streamline tracing because the task seems to require the user to make a series of judgments, starting at the center, whereby the path of a particle dropped in the center is integrated in a stepwise pattern to the edge of the field. Though many algorithms exist in the machine vision literature for contour tracing, we found these to be inappropriate for use in this application. Contour tracing algorithms are generally designed to trace out the boundary of some shape but a streamline tracing algorithm must also be able able to produce a streamline in a field of disconnected contours, such as is the case with the regular arrows. The streamline to be traced will often not follow a visible contour but instead be locate between contours, and will sometimes pass through areas devoid of visual elements. Thus we developed a specialized algorithm that is capable of tracing streamlines that do not necessarily correspond to the boundary of any shape but can pass between visual contours.

Perception is a combination of top-down and bottom-up processes. Bottom-up processes are driven by information on the retina and are what is simulated by Li's model [Li 1998]. Top-down processes are much more varied and are driven in the brain by activation from regions in the frontal and temporal cortex that are known to be involved in the control of pattern identification and attention [Lund 2001]. All of the flow visualizations evaluated by [Laidlaw et al. 2001], except for LIC, contain symbolic information regarding the direction of flow along the contour elements (e.g. an arrowhead). In a perpetual/cognitive process this would be regarded as a top-down influence. At present our model does not deal with symbolic direction information but it does do streamline tracing once set in the right general direction.

Streamline tracing is a combination of top-down and bottom-up processes. Broadly speaking, top-down processes reflect task demands and the bottom-up processes reflect environmental information. In our case, the bottom-up information comes from the different types of visualization, while the top-down information is an attempt to model the cognitive process of streamline pathway tracing. Contour integration was modeled using the following iterative algorithm.

**ALGORITHM 1:** Iterative Algorithm

*current\_position* ← center

*current\_direction* ← up

*current\_position* is inside circle

**while** *current\_position* ***is inside circle***, **do**

*neighborhood*  ← all grid hexes within two hexes from *current\_position*

**for** ***each*** *hex* ***in*** *neighborhood*, **do**

**for** ***each*** *neuron* ***in*** *hex* **do**

convert *neuron\_orientation* to *vector*

scale *vector* by *neuron\_excitation*

*vector\_sum* ← *vector\_sum* + *vector*

**end**

**end**

normalize *vector\_sum*

*current\_position* ← *current\_position* + *vector\_sum*

*current\_direction* ← *vector\_sum*

return *current\_position*

**end**

The algorithm maintains a context that contains a current position and direction. Initially, the position is the center, and the direction set to upward. This context models the higher-order, top-down influence on the algorithm that results from the task requirements (tracing from the center dot) and the directionality which in our experiment was set to be always in an upwardly trending direction.

The algorithm traces the contour by repeatedly estimating the flow direction at the *current\_position* and moving the position a small distance (.5 hex radii) in that direction. The flow direction is calculated from the neural responses in the local neighborhood of the *current\_position*. The excitation of each neuron is used to generate a vector whose length is proportional to the strength of the response and whose orientation is given by the receptive field orientation. Because receptive field orientations are ambiguous as to direction (for any vector aligned with the receptive field, its negative is similarly aligned). The algorithm chose the vector most closely corresponding to the vector computed on the previous iteration. Vectors are computed for all neurons in hypercolumns within a 2-hexes radius of the current position; they are summed and normalized to generate the next *current\_position*.

Some changes were made from the method published by [Pineo and Ware 2008]. Previously, the algorithm considered only a single hex cell at each iteration of the algorithm. We found that this would occasionally cause unrealistically large errors in streamline tracing. For example, on visualizations with arrowheads, the neural network might yield a very strong edge orthogonal to the flow field positioned at the back of an arrowhead. If the algorithm considered only the edges at this point, it may make a significant error, despite the edges in nearby positions indicating the correct direction. We felt that creating an average over *neighborhood* was the more correct approach, and we found closer agreement with human performance with this change.

## Qualitative Evaluation

Four different flow visualization methods were used in our evaluation of the theory. These were implementations of four of the six used by [Laidlaw et al. 2001]. We chose to investigate a regular arrow grid because it is still the most commonly used in practice and a jittered arrow grid because of the arguments that have been made that this should improve perceptual aliasing problems [Turk and Banks 1996]. We added Line Integral Convolution (LIC) because of its widespread advocation by the visualization community [Cabral and Leedom 1993] and head-to-tail aligned streaklets because of Laidlaw et al.'s finding that is was the best and the theoretical arguments in support of this method [Ware 2008]. Note that Laidlaw et al. used Turk and Banks algorithm to achieve aligned arrows on equally spaced streamlines while we used Jobard and Lefer's [Jobard and Lefer 1997] method to achieve the same effect and we used streaklets without an arrowhead [Fowler and Ware 1989].

 

Fig. 3a. Regular arrows. Fig. 3b. Jittered arrows

V1 is known to have detectors at different scales. However, to make the problem computationally tractable we chose only a single scale for the V1 and designed the data visualizations with elements scaled such that they were effectively detected by the gabor filter used by the model. The widths of the arrows and streaklets were chosen to be smaller than the central excitatory band of the gabor filter. This allowed the edge to be detected even if not precisely centered on the receptive field of the neuron. The spatial frequency of the LIC visualization is defined by the texture over which the vector field is convoluted. Our texture was created by generating a texture of random white noise of one-third the necessary size and scaling it up via. interpolation. The resulting spacial frequency of the LIC visualization was of a scale that was effectively detected by the gabor filters of the model.

4.1.1 *Regular Arrows (Figure 3a).* This visualization is produced by placing arrow glyphs at regular spacings. The magnitude of the vector field is indicated by the arrow length, and the flow direction by the arrow head. The grid underlying the regular arrows is apparent to humans, but the edge weights of the model show no obvious signs of being negatively affected. In fact, the regularity ensures that the arrows are well spaced, preventing any false edge responses that might be produced by the interference of multiple arrows. We can expect that nontangential edge responses will be produced by the arrowheads and these will lead to errors in the streamline advection task.

4.1.1.1. *Jittered arrows (Figure 3b).*This visualization is similar to the regular arrows, but the arrows are moved a small random distance from the regular locations. While composed of the same basic elements as the regular grid, we see instances where nearby arrows interfere with each other and produce edge responses nontangential to the flow direction. Also, as with gridded arrows, the arrowheads will excite neurons with orientation selectivity nontangential to the flow. This can be seen in Figure 4a. In this figure, we can see orthogonal neural excitation to each side of the upper arrow, caused by the back edge of the arrowhead (blue circles). We can also see excitation caused by the interference of two arrows at the bottom right (green circle). These nontangential responses are much stronger than those found in the aligned streaklets visualization (Figure 4b).

 

Fig. 4a. Closeup of neural response to arrowheads Fig. 4b. Closeup of neural response to aligned streaklets.\*\*

# DISCUSSION

The overall agreement between the pattern of results for human observers and the V1-based model provides strong support of the perceptual theory we outlined in the introduction. The aligned arrows style of visualization produced clear chains of mutually reinforcing neurons along the flow path in the representation, making the flow pathway easy to trace as predicted by theory.

The fact that LIC produced results as good as the equally spaced streamlines was something of a surprise, and this lends support to its popularity within the visualization community. While it did not produce as much neuron excitation as the aligned arrows method, this was offset by the lack of nontangential edge responses produced by glyph-based visualizations. However, its good performance was achieved only because our evaluation method ignored the directional ambiguity inherent in this method. [Laidlaw et al. 2001] found this method to be the worst and there is little doubt that had we allowed flow in any direction, up or down, human observers would have found pathways with close to 180 degrees of error half of the time.

The performance of both the model and the human test subjects is likely to be highly dependent on the underlying vector field used. As described in Section 5.1.6, the vector field was generated by interpolating between an 8x8 grid of random, but generally upward pointing vectors. A consequence of this is that when adjacent vectors in this grid point somewhat toward each other, the vector field forms an area of convergence. This convergence area tends to funnel neighboring streamline paths together, reducing error in streamline tracing (Figure 3 is an example of this). Thus, the overall accuracies of both the model and human subjects may be higher than might be might be observed using a vector field without such convergence zones.

We were surprised that the computer algorithm actually did better at the task than human observers. One reason for this may have been that humans would have to make saccadic eye movements to trace a path, whereas the computer did not. For the patterns we used, it is likely that the observers had to make fixations on several successive parts of a path, and errors may have accumulated as they resumed a trace from a previous fixation. Nevertheless, we feel that the algorithm could easily be adjusted to make it give results closer to human subjects. A more sophisticated approach would be to simulate eye fixations.

The model we applied is a considerable simplification over what actually occurs. It only uses the simplest model of the simplest orientation sensitive neurons, and fails to include cortical magnification, among other shortcomings. Real cortical receptive fields are not arranged in a rigid hexagonal grid as they are in Li's model. Furthermore, the neurons of V1 respond to many frequencies, however our model only uses one in its present form. In addition, besides the so-called simple cells modeled by [Li 1998], other neurons in V1 and V2 called complex and hypercomplex cells all have important functions. For example, end-stopped cell respond best to a contour that terminates in the receptive field and understanding these may be important in showing how the direction of flow along a contour can be unambiguously shown. Moreover, visual information is processed through several stages following the primary cortex, including V2, V4 and the IT cortex. Each of these appears to abstract more complex, less localized patterns. Researchers are far from having sufficient information to model the operations of these stages all of which may have a role in tracing contours. Nevertheless, the results are compelling and there are advantages in having a relatively simple model. We have plans to add some of these more complex functions in future versions of the model.

# TYPICAL REFERENCES IN NEW ACM REFERENCE FORMAT

A paginated journal article [Abril and Plant 2007], an enumerated journal article [Cohen et al. 2007], a reference to an entire issue [Cohen 1996], a monograph (whole book) [Kosiur 2001], a monograph/whole book in a series (see 2a in spec. document) [Harel 1979], a divisible-book such as an anthology or compilation [Editor 2007] followed by the same example, however we only output the series if the volume number is given [Editor 2008] (so Editor00a’s series should NOT be present since it has no vol. no.), a chapter in a divisible book [Spector 1990], a chapter in a divisible book in a series [Douglass et al. 1998], a multi-volume work as book [Knuth 1997], an article in a proceedings (of a conference, symposium, workshop for example) (paginated proceedings article) [Andler 1979], a proceedings article with all possible elements [Smith 2010], an example of an enumerated proceedings article [Gundy et al. 2007], an informally published work [Harel 1978], a doctoral dissertation [Clarkson 1985], a master’s thesis: [Anisi 2003], an online document / world wide web resource [Thornburg 2001], [Ablamowicz and Fauser 2007], [Poker-Edge.Com 2006], a video game (Case 1) [Obama 2008] and (Case 2) [Novak 2003] and [Lee 2005] and (Case 3) a patent Scientist 2009], work accepted for publication [Rous 2008], ‘YYYYb’-test for prolific author [Saeedi et al. 2010a] and [Saeedi et al. 2010b]. Other cites might contain ‘duplicate’ DOI and URLs (some SIAM articles) [Kirschmer and Voight 2010]. Boris / Barbara Beeton: multi-volume works as books [Hörmander 1985b] and [Hörmander 1985a].

APPENDIX

With closest point to a given set of lines we intend the point having the minimum Euclidean distance with respect to those lines. Typically, this problem is formulated using Plücker coordinates. Instead, here we compute this point by solving the problem in a closed form, since the resulting matrices are not ill-conditioned in our case. More precisely, by indicating the set of *n* lines with

 (2)

where *Oi* is the origin of the *i*th line and *di* is the corresponding direction (normalized), we found the closest point by minimizing

 (3)

The distance  can be written as

 (4)

The minimization is obtained by substituting (4) in (3), and imposing the derivative to zero. After some simple algebra, we obtain the final formulation:

 (5)

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Online Appendix to:  
Neural Modeling of Flow Rendering Effectiveness[[2]](#footnote-2)

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A. Analysis of Invalid Trials

A.1. Results

Invalid trials were previously defined as those trials in which the subject pressed the space bar to end the trial without first bringing the virtual finger to a stop. The number of invalid trials for each subject is presented by feedback condition in Figure 12. Due to the irregular distribution of the data, no significance test was run. However, the figure shows two notable features. First, Subject 6 had more invalid trials than any other subject. Second, more invalid trials occurred under the proprioceptive-only (NV + P) feedback condition than any other.

A.2. Discussion

Although the number of invalid trials is not directly related to task performance, we now consider any trends that may be seen in this information. No statistical tests were done with this data, but some inferences can be drawn from the invalid trial counts in Figure 12. The only obvious trend is that the NV + P condition appears to have the most invalid trials, which is the case for all but two subjects. In the post-experiment survey, one subject commented on this trend, saying that with only proprioceptive motion feedback it was hard to tell if the finger was moving or not. This might be a result of a larger threshold for absolute motion detection for proprioceptive feedback than for visual feedback. This difficulty in stopping the finger did not appear to affect the ease of use ratings provided by subjects, as no correlation was observed with invalid trial counts.

It is interesting to note that the no-feedback condition (NV + NP) had fewer invalid trials than the proprioceptive-only condition (NV + P), especially in light of the findings of Ghez et al. [1990] that deafferented individuals tend to display endpoint drift in non-sighted targeted reaching movements (equivalent to NV + NP condition) while neurologically normal individuals do not (equivalent to NV + P condition). A notable difference between our study and the study by Ghez et al. is the availability of kinesthetic feedback from the thumb pressing on the force sensor, which indicates the magnitude of the applied force, that is, the movement command in our study. Thus, under the no-feedback condition, subjects could use this information to learn to apply grasping forces within the dead zone to stop finger movement. When motion feedback is available, subjects are likely focusing more on the feedback than on the forces applied, since the feedback allows them to achieve better accuracy. Thus, at the end of a trial, subjects are most likely using this feedback as an indicator of zero velocity rather than attending to the applied force. When visual feedback is available, it is easy to determine whether the finger is moving or not; however, when only proprioceptive feedback is available, the finger can be moving slowly without the subject being aware of its motion. This explanation would result in a larger number of failed trials for the NV + P condition than for any other, as observed.

1. [↑](#footnote-ref-1)
2. © 2010 ACM 1544-3558/2010/05-ART1 $15.00

   DOI:http://dx.doi.org/10.1145/0000000.0000000 [↑](#footnote-ref-2)