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Unobtrusive In-Home Assessment by Means of Everyday Computer Mouse Usage

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Abstract

An important component of future proactive healthcare is the detection of changes in the individual's physical or cognitive performance, especially for aging and for those with neurodegenerative diseases. For a variety of reasons, the current techniques for neuropsychological assessment are not suitable for continuous monitoring and assessment. This paper proposes a technique for continuous monitoring of behaviors that could potentially be used to complement the traditional assessment techniques. In particular we monitor the movements of a computer pointing device (mouse) to assess cognitive and sensory-motor functionality of human users unobtrusively. The focus of this paper is on an approach that can be used to identify moves so that they can later be used as the basis for constructing sensory-motor measures. Due to the nature of the data the distinction between moves and pauses between moves is not immediately apparent. The segmentation of the data into moves is done by constructing an estimated distribution of the mouse cursor velocity for the entire computer session and locating a particular minimum which indicates a likely point of division between active moves and inter-move intervals. We analyzed computer usage data for 113 elderly participants over a period of two years, and the technique applied to that data was able to divide data from a session of computer usage into a series of mouse moves in 98% of observed computer sessions with a physically sensible value for the cutoff dividing moves from stops.

I. Introduction

Living into old age with a high quality of life is something most everyone wants. However providing adequate care while keeping costs under control has become an important issue [1]. Several methodologies for using home monitoring and assistive technologies for older adults have been proposed [2, 3]. A key aspect of any methodology is the proper assessment of the various aspects of individual performance.

Individual assessment may be viewed as occurring along a spectrum of possibilities. At one end of the spectrum are assessments that take place in a clinical visit. In this case, the individual must take the time and effort to go to a clinic where the various measurements will be made by trained staff. The assessments will be carefully delineated and the staff will ensure that the task is being executed correctly by the individual. This sort of assessment typically results in infrequent though reliable and well understood measures of individual performance.

One may mitigate the problem of infrequency somewhat by creating self-administering forms of the clinical tests which the individual may take in-home. Some of the certainty that the individual is performing the desired task as intended is lost with the absence of some form of supervision. Moreover, as the tasks themselves are typically relatively simple, individuals are likely to find frequent testing somewhat tedious, requiring some kind of regular reminder to take the tests.

The in-home tasks may be allowed to be more complicated (such as taking the form of simple computer games [4]) in order to keep them interesting to the individuals. Ideally, if they are interesting enough, frequent testing becomes less burdensome. Unfortunately, as these become more interesting to participants, analysis becomes more difficult as the restriction to a single task gives way to a confluence of a variety of tasks making up performance.

Finally, at the opposite end of the spectrum from assessment via clinical visits is passive assessment of daily behaviors [5]. While the frequency of tasks or activities is much less of an issue, the lack of specific knowledge of the activity and its motivation and context becomes more acute.

Our interest here is to use the individual's everyday computer usage as an in-home tool for assessing individual performance. Although we also have data on general computer activity, typing speed, and word complexity, the data being considered for this paper are restricted to the position of the mouse cursor on the computer screen as a function of the time. While further information about what the participant is doing on the computer (such as the application being used) is available, they have been ignored so that the structure of the mouse cursor trajectory alone may be studied.

Fundamentally, the mouse is experienced by the user as tool which they use at times to interact with the computer, and at other times more passively move while they engage with material on the computer monitor. Usage of the mouse can be thought of as consisting of a series of mouse moves. Each mouse move is itself a specific and continuous physical process initiated and concluded by the user and forming a continuous whole. Thus moves form natural physical units within the computer usage.

Once moves have been identified one has not only identified natural units of computer usage, but also specific physiological processes generated by the user. This suggests that one my construct both cognitive and physical measures from them. Some examples could be an activity measure based on the number of moves per hour, or an efficiency measured based on the trajectories taken by the mouse. We postulate that the active and more purposeful moves will more closely approximate a user’s sensory-motor speed. Thus, our goal is to measure active mouse movements and to develop an algorithm for distinguishing between active and passive usage, being given only the mouse cursor trajectory.

II. Identifying Mouse Moves

A mouse move is a continuous physical process where the mouse begins in some position with no motion, is accelerated by the computer user in some direction moves at non-zero speed for some period of time, and is finally decelerated by the user and brought to a halt at some desired position. So the move itself is a continuous physical process with a specific beginning and ending. In identifying mouse moves, our aim is to identify segments of the mouse data corresponding to individual physical processes of this type.

The data used in this project consists of unevenly sampled time series of mouse cursor position data from single computer sessions which we would like to classify into individual movements of the mouse by the user. A ‘session’ is understood to be a single period of usage beginning with a login by the user and ending when activity has been observed to have halted prior to the next login on the computer. The present goal is to identify a metric motivated by the structure of the mouse data itself which may be used to distinguish *active moves* from *inter-move intervals* within the observed data.

The active moves should largely coincide with what is intuitively thought of as moves of the mouse by the user, that is, with periods of intentional motion of the mouse. As will be seen active moves might not include moves made by the user which are too slow. The inter-move intervals are intuitively the periods of time between active moves. They are expected to include stops or pauses in motion by the user as well as very slow movements of the mouse if those occur. Due to the nature of the data, there is ambiguity as to whether a stop or very slow motion is occurring.

When a computer session is started, the initial position of the mouse cursor and the time is recorded. Thereafter, subsequent positions and times are recorded whenever the cursor's position exceeds a distance of 5 pixels from the last recorded position using a Manhattan distance metric. The computer itself has a minimum time interval τ = 16msec in which it may make this comparison. As a result, the recorded cursor data fall into two domains. For faster cursor speeds, the positions and times will be recorded at regular time intervals τ, but the change in position between adjacent data-points will be some distance of at least 5 pixels. Conversely, for slower cursor speeds, the positions and times will be recorded at regular changes of position of 5 pixels, while the time between adjacent data-points will be some positive integer multiple of τ.

The mouse cursor data for a particular computer session may be thought of as a single trajectory of position and time data that has been unevenly sampled in time X_i, Y_i, T_i. Using these data we are able to construct an approximation to what the trajectory would have looked like had it been regularly sampled. This is done by assuming motion of constant velocity along a straight line between recorded data-points and interpolating the required values. A sample rate equal to the fastest rate at which the computer records the mouse data, that is τ, is chosen. This process yields an interpolated mouse cursor trajectory x_j, y_j, t_j for the session.

The trajectory of the mouse cursor may now be considered in terms of the sequence of velocities on each interval between consecutive observations v_j. Although the cursor motion has so far been treated as a single trajectory, we expect it to be dividable into active moves and inter-move intervals. Thus, it is expected that the cursor trajectory should divide itself into intervals of high velocity when the user is moving the mouse, and intervals of low velocity when the user is pausing or doing something not involving the mouse or making a quick stop in motion. We would like to identify the cut velocity v_{cut} which can be used to demarcate the boundary between movements and pauses. It is safe to say that intervals requiring more than 5sec to move 5 pixels should be pauses so these are trimmed and we restrict to considering the distribution of the remaining data. Figure 1 shows the kernel smoothed density estimate for the data set $\log_{10} v_j$ for a typical session.

The density is multimodal with a particularly low local minimum at about 64 pixels/sec indicated. The minimum of interest may be identified by searching the kernel smoothed density estimate for the appropriate local minimum. This may be done by first restricting to a region surrounding the expected location of the minimum. We have used the region of velocities between 10 pixels/sec and 1000 pixels/sec. The boundaries of this region are sufficiently slow or fast as to be expected to belong to the domain of pauses or moves respectively. The density may now be searched on this region for the lowest local minimum not lying on the boundaries. This minimum is taken to be the cut velocity v_{cut}.

Once v_{cut} has been determined, we may return to the original data X_i, Y_i, T_i, and cluster the observations into individual mouse moves. A velocity may be defined on each interval between consecutive observations in the observed mouse cursor trajectory giving a set of velocities V_i. Intervals with $V_i < v_{cut}$ are identified as pauses and the sets of observations between pauses are identified as individual moves.

Often it is found that some moves identified by this process consist of a single observation. These points are taken to be due to noise and dropped with the pauses on either side combined into a single longer pause.

III. Observed Computer Usage

We consider the recorded computer usage of a cohort of 113 participants (aged 86 +/− 5 years at the beginning of the period being considered) each observed for a period of two years. Each participant lived alone. A total of 47967 computer sessions were observed among all participants. The procedure to find a cut velocity v_{cut} was applied to all sessions. The procedure failed to find a value in 791 cases. This is to say, in about 98% of sessions an appropriate cut velocity was found and mouse data from the session was able to be divided into mouse moves. Figure 2 shows the kernel smoothed density estimate for all successfully calculated cut velocities across all participants.

In the case of sessions in which a value v_{cut} was successfully calculated, this value may be used to cluster the observations into active moves. Figure 3 shows an 8 second extract from an observed computer session with the identified moves indicated. In this case v_{cut} was 66 pixels/sec.

IV. Discussion

We have observed that, for most computer sessions, the interpolated mouse cursor trajectory exhibits a multimodal distribution in the logarithm of the velocity. This distribution usually has a local minimum around 66 pixels/sec. A velocity of this magnitude is a reasonable candidate for the dividing line between active moves and inter-move intervals, being a speed which is low when considered against normal usage but still fast enough that one may envision exceptionally slow mouse movements occurring at this speed.

When the cases where a local minimum in the region of velocities between 10 pixels/sec and 1000 pixels/sec failed to be found, it appeared the session was fairly short. A plausible scenario in this case would be logging into the computer to check if one has email and, upon finding one does not have any, logging out immediately.

For sessions with more activity, the desired minimum could be found. This value could then be used to cluster the observations into a series of mouse moves. As the value is, as expected, a borderline velocity value, there are cases where upon direct inspection of the observation data one might feel an identified move which is exceptionally long ought to be divided into separate moves, or two moves should be combined into one. We expect that further criteria may be developed to better deal with the borderline cases.

Further problems arise in situations where the computer's operating system fails to immediately recognize changes in the mouse position, or the computer causes the cursor to move without that motion following from motion of the mouse. In the first case, the cursor remains frozen in place despite motion of the mouse but is eventually suddenly moved to the correct position resulting in longer pause followed by sudden high velocity motion not reflecting user input. The second case appears as a constant slow drift of the cursor across the computer screen which persists until the mouse is moved by the user. Such instances should be detected and removed from the data. Other analogous problem artefacts are also likely to occur.

The intent of the method is to identify segments of the mouse data corresponding to the physical process of accelerating the mouse from a stopped position, moving it, and decelerating to stop it in a new position. This is purely physical process of the arm and hand moving the mouse. Related to this is the cognitive process of selecting a position for the mouse to be moved to and initiating the motion. There is not any immediate reason that an individual cognitive process as the one described need correspond to an individual physical process like the one described. That is to say, it is entirely possible that a single cognitive process of moving to a particular destination could be physically realized as a series of physical moves of the mouse with very short stops between them.

We should thus understand the identified moves as corresponding to specific physical moves of the mouse. The validity of the technique needs to be demonstrated by showing that the identified moves do correspond to the physical movements (in the sense of a move being a continuous process as described earlier). With this demonstrated, the measures constructed to assess individual performance will have a firm, physical foundation.

V. Conclusion

We have developed a technique for taking raw mouse trajectory observations and identifying the active purposeful mouse movements. This is done by identifying a structure present in the distribution of the logarithm of the sampled velocities in the mouse trajectory. The velocity found this way is about where the borderline between active moves and inter-move intervals might be expected to be. Active moves are then identified by deciding whether the interval between two observations would have a velocity above or below that borderline velocity.

While this appears to largely identify active moves that seem intuitively plausible, there do appear outlier moves which seem unintuitively long. Likely a somewhat more complicated technique is needed to remedy this problem.

We plan to continue this work by collecting appropriate ground truth data which gets to the physical characteristics of a mouse move. Comparing the mouse moves identified by the method described here against this ground truth will allow us to demonstrate whether identified moves have the required physical characteristics, and ensure that the method is grounded in more than intuitive plausibility, and that measures constructed from the output of this method are well-founded.

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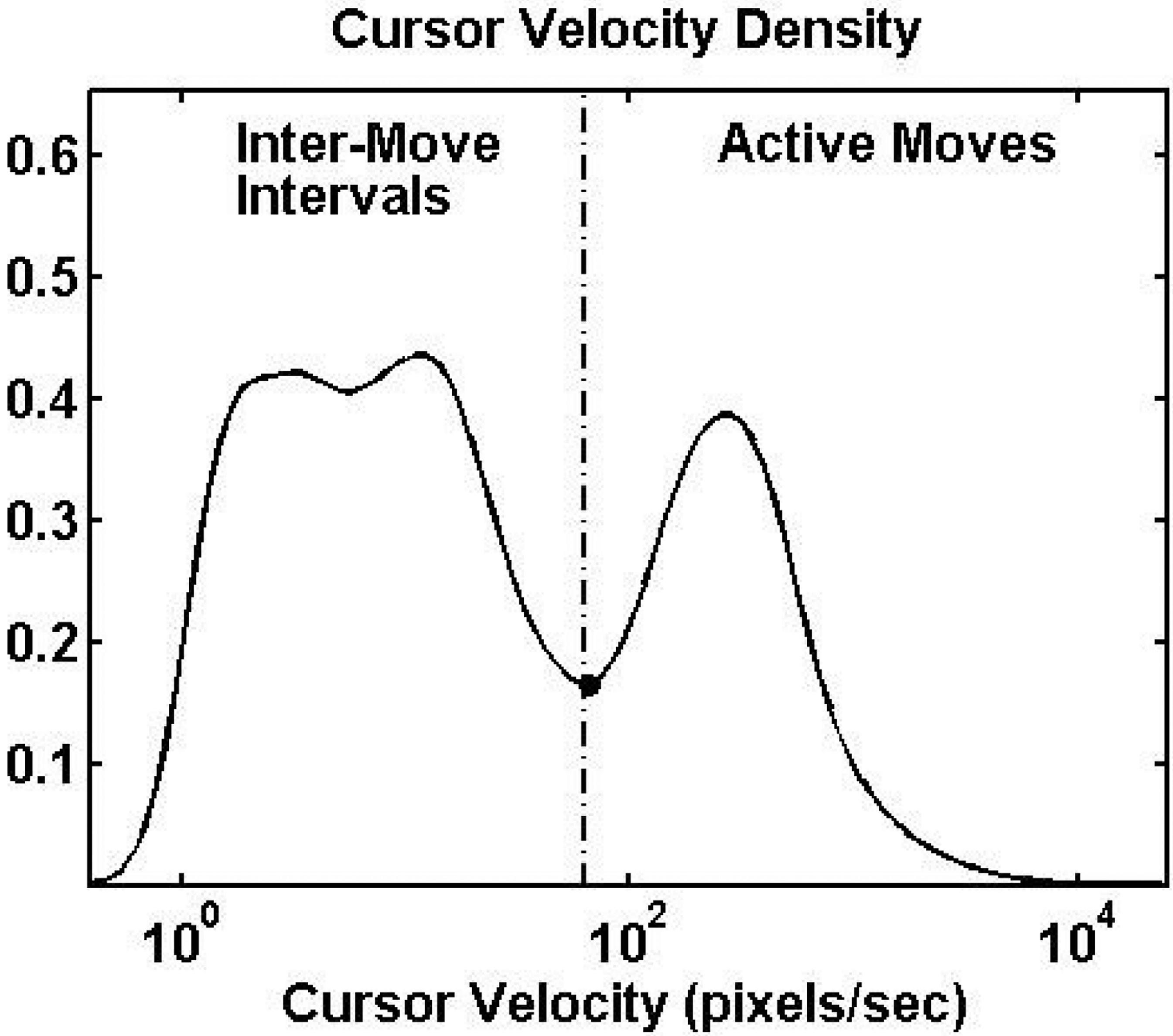

Fig. 1.
The kernel smoothed density estimate for logarithm of the cursor velocity for a single computer session showing the proposed division of the data into active moves and inter-move intervals. The dotted line shows the cut velocity, that is, the boundary between these regions.

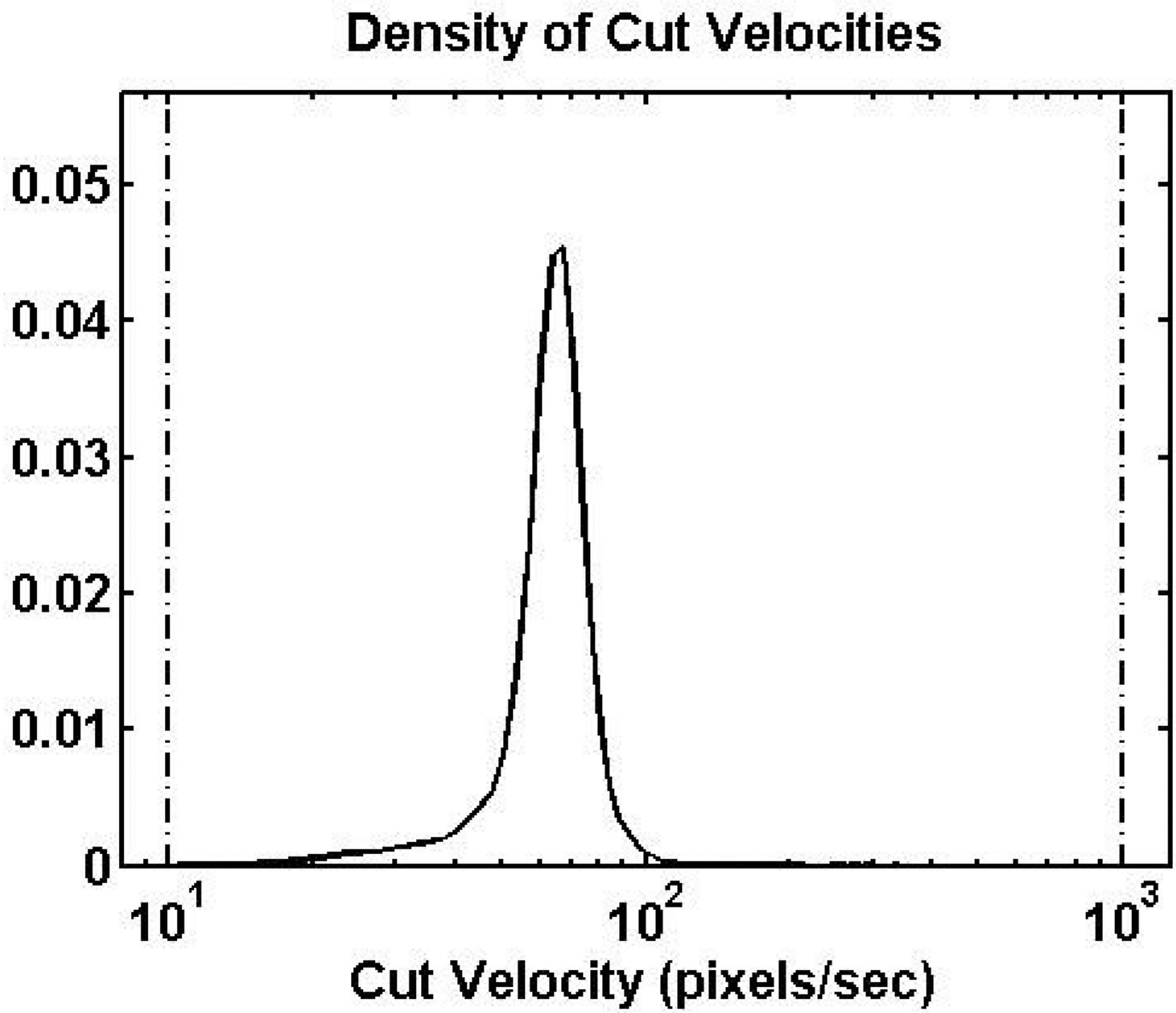

Fig. 2.
The kernel smoothed density estimate for logarithm of the calculated cut velocity across all participants for all cases in which a cut velocity was found. This is the density of values across 47176 computer sessions. The dotted lines indicate the boundaries of the region to which search was restricted.

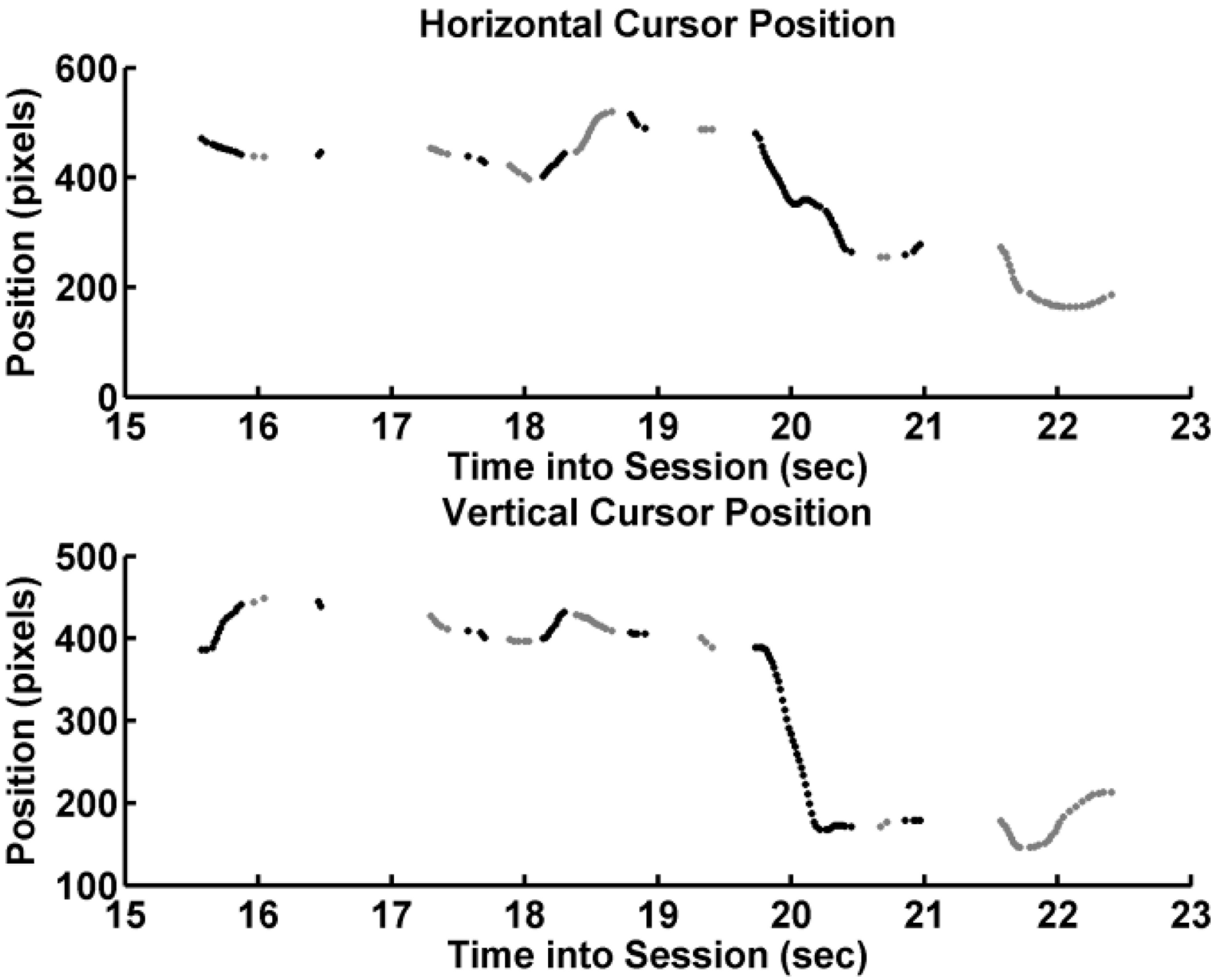

Fig. 3.

A portion of mouse movement taken from a computer session with moves identified and indicated in alternating clusters of black and grey. The time indicated is the number of seconds from the beginning of the session.