# Psychophysical evidence for fast region-based segmentation processes in motion and color

### (visual perception/figure–ground segregation)

PER MØLLER AND ANYA C. HURLBERT

Physiological Sciences, Medical School, University of Newcastle-upon-Tyne, Newcastle-upon-Tyne, NE2 4HH United Kingdom

**ABSTRACT**    Theories of image segmentation suggest that the human visual system may use two distinct processes to segregate figure from background: a local process that uses local feature contrasts to mark borders of coherent regions and a global process that groups similar features over a larger spatial scale. We performed psychophysical experiments to determine whether and to what extent the global similarity process contributes to image segmentation by motion and color. Our results show that for color, as well as for motion, segmentation occurs first by an integrative process on a coarse spatial scale, demonstrating that for both modalities the global process is faster than one based on local feature contrasts. Segmentation by motion builds up over time, whereas segmentation by color does not, indicating a fundamental difference between the modalities. Our data suggest that segmentation by motion proceeds first via a cooperative linking over space of local motion signals, generating almost immediate perceptual coherence even of physically incoherent signals. This global segmentation process occurs faster than the detection of absolute motion, providing further evidence for the existence of two motion processes with distinct dynamic properties.

A fundamental goal of vision is to locate, characterize, and recognize objects. But to determine "what" is "where" the visual system must first determine which parts of the image belong together. This is the problem of image segmentation, central to both human and machine vision. How the brain implements image segmentation is not known, although various physiological mechanisms have been proposed (for a review, see ref. 1).

Objects are distinguished not only by feature contrasts at their boundaries with the background but also by the similarity of feature properties within their boundaries. Two types of segmentation process may exist to exploit these two fundamental distinctions: a local edge-based process that marks differences in visual attributes and a global region-based process that finds homogeneous areas by integrating information about attributes over space. Edge detection is fundamental to many machine vision algorithms (2) but rarely flawless on its own in segmenting an image into relevant regions. In natural images, edges are disrupted by noise, occlusions, and interference from other edges. Edges are also ambiguous: luminance edges, for example, may arise from many distinct physical causes. Therefore, edge detection segmentation algorithms typically require fragile and adaptive adjustment of thresholds, iterations on multiple spatial scales, and special line-completion methods (3, 4). Region-based segmentation algorithms typically "grow" regions from seed patches, accreting all those surrounding areas that share the same properties as the seed, the end result being a set of internally homogeneous regions (5). But region-based algorithms also face

problems in defining and setting thresholds for homogeneity, particularly in noisy or complex images characterized by multiple attributes.

Recent computer algorithms for image segmentation address the dual problems of region-based and edge-based processes by combining them (4, 6, 7). There is some experimental evidence that both types of segmentation process also act in human vision. The importance of similarity in perceptual grouping was emphasized by the Gestalt psychologists, whose laws of figural unity included spatial contiguity, conformity of movement or depth, and uniformity of color and texture (8). Similarity of features also figures importantly in modern theories of segmentation and binding (e.g., ref. 9). Recent psychophysical studies in humans have emphasized the role of discontinuities in image segmentation and demonstrated that local differences in motion, color, texture, depth, and luminance may drive image segmentation (for reviews, see, e.g., refs. 10–12). Yet most human psychophysical studies of image segmentation have not focused on the distinction between edge-based and region-based segmentation, with some notable exceptions (13, 14). Mumford *et al.* (14) showed that in the luminance domain, the human visual system uses a hybrid algorithm that is sensitive both to the luminance variation within a region and to the sharpness of its edges.

In the natural world, the human visual system must combine information from different attributes to find object boundaries and distinguish surfaces. We ask herein whether the segmentation processes based on different attributes are themselves different. Although relative motion is a compelling cue for image segmentation, for example, it is debatable whether the relative motion signal is computed by an edge-based or region-based mechanism (15, 16). Much evidence suggests that motion and color information are conveyed by two distinct functional streams (17, 18) although recent anatomical and physiological results (19, 20) indicate substantial cross-talk between them. It is therefore interesting to determine whether fundamental differences in segmentation by motion and color exist. Herein we compare characteristics of edge-based and region-based segmentation processes for color and motion, by manipulating both local feature contrast and similarity signals in a figure–ground segregation task.

Because local feature contrast may occur on a smaller spatial scale than similarity signals, the distinction between edge-based and region-based processes is also a distinction between different spatial scales. The importance of spatial scale for a number of low-level spatial vision tasks has been studied by Watt (21), who suggested that the visual system scans from coarse to fine spatial scales directly after stimulus onset. From visual recognition studies, Navon (22) concluded that global structure emerges earlier in the percept than local features. Herein we also examine the temporal characteristics of the two hypothesized segmentation processes, for motion and for color.

Abbreviation: CIE, Commission Internationale de l'Eclairage.

## METHODS

Observers performed a two-alternative-forced-choice (2AFC) figure–ground discrimination task on a 6.5° square array of 1024 randomly positioned dots (each 4.7' square) against a dark gray or black field in a black surround. The target was a vertical band of dots that appeared either to the left or right of midline and was distinguished from the background by a different distribution of dot speeds or colors (Fig. 1). We measured target detection thresholds by varying the difference between the target and background distributions, using the method of constant stimuli. Stimuli were generated on a Silicon Graphics computer and displayed on a linearized EIZO flexscan T560i-T RGB monitor.

The four observers sat at chin rests and viewed the stimuli binocularly in a darkened room from a distance of 1.14 m. The observers began each trial with a button press, after which a small central white fixation cross appeared for 500 msec. The cross was extinguished and a uniform dark gray background appeared for 300 msec (a blank interval), followed by the stimulus for a specified duration between 17 and 200 msec, which was then followed by a second blank interval. A mask, consisting of a square array of moving dots with random colors and speeds, then appeared for 67 msec. The stimulus onset asynchrony (SOA) between stimulus and mask onset was fixed at 300 msec. The observer was given unlimited time to make a response after the mask. Observers were instructed to press the left (right) mouse button if the target appeared to the left (right) of midline and were asked to keep fixation at the location of the fixation cross throughout the complete trial.

**Motion Stimuli and Measurements.** In all motion experiments (but one; see experiment III below), the target and background dots moved vertically upward with speeds drawn from $\delta$ distributions; that is, speeds were uniform within each region. All dots were reddish [Commission Internationale de l'Eclairage (CIE) $x, y$ values = 0.45, 0.35; luminance = 10 cd/m²] against a black field. We measured thresholds for target detection as a function of difference between the target and background speeds. In every case, since the background dots moved, detection of motion *per se* was not sufficient for target detection.

To vary the strength of region-based signals while keeping edge information constant, we varied the size and eccentricity of the target stripe. If edge information were the only signal to segmentation, then target detection thresholds should depend only on the detectability of its edges. For example, if we assume that thresholds for edge detection increase with increasing eccentricity, a narrow target should be detected more easily
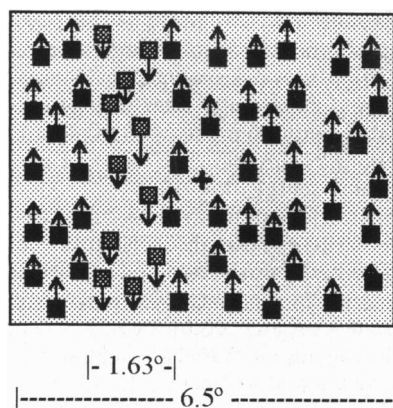
than a broader target if the inner edges of each are at the same eccentricity. In experiment Ia, we therefore measured target detection thresholds for two conditions: (*i*) inner edges of both narrow (0.32°) and broad (1.44°) targets fixed at 1.63°, with outer edges at 1.95° and 3.07° respectively; and (*ii*) outer edges of both narrow and broad targets fixed at 3.07°, with inner edges at 2.75° and 1.63°, respectively. The background dot speed was 1.6°/sec and stimulus duration was 50 msec.

In experiment IIa, we varied target width (0.16°, 0.32°, 0.48°, and 0.72°) and stimulus duration (34, 50, 67, 100, and 200 msec). Background dots moved with speed 1.6°/sec and the target's inner edge was at eccentricity 1.63°. The measurements for target widths of 0.16° and 0.72° were also performed for a background dot speed of 4.8°/sec.

In experiment III, we measured motion segmentation thresholds for targets defined by a speed distribution that overlapped with the speed distribution of the background. Background dots (whose positions were selected at random) were assigned speeds from a Gaussian distribution of standard deviation 0.6°/sec, centered on 1.6°/sec. Target dots were assigned speeds from Gaussian distributions of standard deviation 0.6°/sec, with mean value ranging from 1.73° to 4.8°/sec. Target width was fixed at 0.48°; stimulus duration was varied from 34 to 200 msec.

In experiment IV, we measured motion detection thresholds as a function of stimulus duration for a 6.5° square array of 1024 dots moving uniformly vertically upward, as well as, for one observer, for a rectangular array of width 0.72° positioned with its inner edge 1.63° eccentric to the central fixation point. Size, luminance, and color of dots were as above. We performed this measurement in a temporal 2AFC paradigm using the same sequence of events as above repeated twice per trial. The two stimulus presentations in each trial were separated by a 200-msec blank interval. In one interval the dots were in motion; in the other, the dots were static. The observer's task was to indicate in which interval the dots appeared to move.

**Color Stimuli and Measurements.** We measured color segmentation thresholds using the same spatial 2AFC procedure as for the motion case. All specifications were as above except that the segmentation signal was defined by a difference only in the dot color distributions for target and background. The dots were static and had a luminance of 6 cd/m² against a dark gray stimulus field of luminance 0.5 cd/m² in a black surround. Background dots were assigned colors from a uniform distribution in color space centered on CIE $x, y$ = (0.38, 0.35), with CIE $x$ values ranging from 0.28 to 0.48 and CIE $y$ values ranging from 0.29 to 0.41. The target dots were assigned colors from a set of uniform distributions, each with the same mean and range CIE $y$ value as the background distribution. The CIE $x$ values of the target dots spanned a range of ±0.06 around a mean value taken from the set (0.385, 0.395, 0.405, 0.415, 0.425, 0.435).

Note that the target distribution was completely contained within the background distribution for four of the six mean $x$ values and extended only very little outside the background distribution for the other two mean $x$ values. One advantage of using broad overlapping distributions is that the segmentation task cannot be performed by detection of colors of single target dots. When the difference between the target and background mean CIE $x$ values is large enough the target appears vividly distinct in color from the background.

As for the motion case, we varied size and eccentricity of the color targets. In experiment Ib, we compared thresholds for a fixed broad target (1.44°) with those for a narrow target (0.32°) at two eccentricities, aligning its inner and outer edges separately with those of the broad target. Stimulus duration was 67 msec. In experiment IIb, we measured thresholds as a function of stimulus duration (17, 67, 100, and 200 msec) for three target widths (0.32°, 0.72°, and 1.44°). Target inner edges were each at eccentricity 1.63°.



|- 1.63°-|

|---------------- 6.5° ----------------|

FIG. 1. Schematic drawing of stimulus, with inner edge of target at 1.63° eccentric to central fixation cross, shown for reference only. In the motion stimulus, all dots are of same color and luminance. Arrows indicate that target and background dots move with different speeds, drawn from either $\delta$ or Gaussian distributions.

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**Determination of Thresholds.** Each experimental run consisted of 20 trials per target signal value; five runs were completed for each condition, giving a total of 100 measurements for each value for each condition. We determined psychometric functions by fitting cumulative Gaussian function values to the percentage correct responses for the five (motion) or six (color) target signal values. Thresholds were computed as the target signal value yielding 75% correct responses.

## RESULTS

Fig. 2 *Upper* shows how motion segmentation thresholds (expressed as Weber fractions) depend on target size and eccentricity (experiment Ia). The threshold for the narrow target increases with eccentricity and is always larger than that for the broad target. If the targets were detected by edge-based processes alone, one might expect the broad target to be more readily detected than the narrow eccentric target, because its inner edge is less readily detected due to its peripheral location, compared with the inner edge of the broad target. The probability of detecting the broad target should then be no more than the combined probabilities of detecting the central and eccentric narrow targets, with each of which it shares one

edge. (In fact, since the two narrow targets contribute four assumptively independent edges, the probability of detecting the broad target with just two edges should be less.) To compute the predicted threshold for detecting the broad target by probability summation, we compute the combined probability at each signal strength, fit a psychometric function to the combined probabilities, and take the threshold signal as that yielding 75% correct responses. For each observer, the predicted threshold for the broad target from probability summation of the two narrow targets is significantly higher than that observed.

Fig. 2 *Lower* shows how color segmentation thresholds depend on target size and eccentricity (experiment Ib). Again, thresholds for the broad target are smaller than for the narrow target, and, again, detection of the broad target cannot be predicted from probability summation of detection of the two narrow targets (except for observer RS).

Fig. 3 shows thresholds for absolute motion detection (experiment IV) and for motion segmentation (experiment IIa) as a function of stimulus duration for targets of various sizes. The temporal build-up functions for broad and narrow segmentation targets differ strikingly. The curve is almost flat for the broadest target and becomes sharply steeper for target widths smaller than about 0.32°, with thresholds decreasing by a factor of about 3 between stimulus durations of 34 msec and 100 msec. Performance reaches a plateau after about 100 msec. At any given speed difference, a broad target is detected faster than a narrow target. Thresholds for the "noisy" broad target (0.48°) of experiment III, with speed distributions that overlap the background speed distribution, are indistinguishable from those for the 0.48° uniform target, for observer PM. (Similar results were obtained for two other observers with different stimulus parameters).
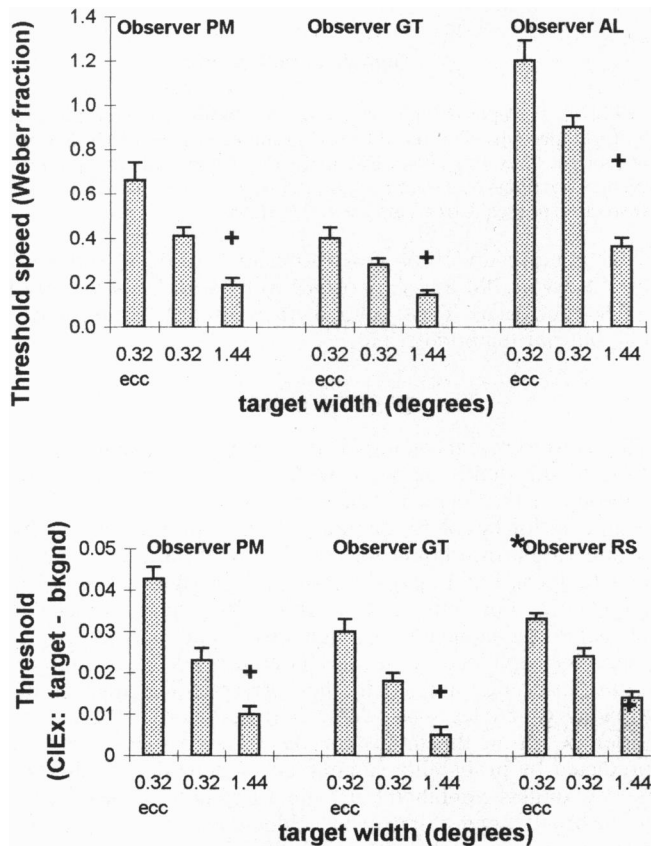


FIG. 2. (*Upper*) Motion segmentation thresholds for uniform targets against uniform backgrounds, for two target widths (0.32 and 1.44°). Narrow target tested at two positions, inner edge at 1.6° and 2.65° (ecc). Background dot speed, 1.6°/sec vertically upwards; stimulus duration, 50 msec. Thresholds are given as Weber fractions, i.e., as the fractional increase in target speed relative to background speed at 75% correct responses. (*Lower*) Color segmentation thresholds for broad distributions of target and background dot colors. Target size and eccentricities are as above. Thresholds are given as the difference between mean CIE$x$ values of the target and background distributions at 75% correct responses. Stimulus duration, 67 msec. Pluses mark thresholds for the 1.44° target predicted by probability summation of the two narrow targets. Error bars show the SEM. *Observer RS is monocular.
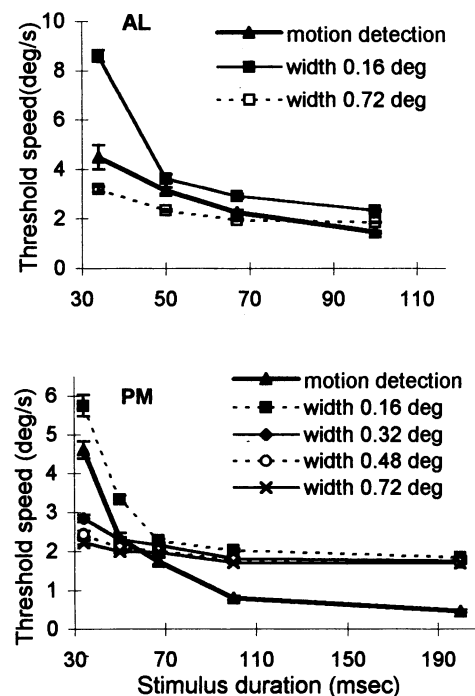


FIG. 3. Motion segmentation thresholds for uniform speed distributions and motion detection thresholds (thick line) as a function of stimulus duration and target size (observers PM and AL). For motion segmentation, all background dots moved upward at 1.6°/sec. For motion detection, all dots in the 6.5° square field moved uniformly upward in one interval and were static in the other. Thresholds are given as target speed in the segmentation task and dot speed in the detection task, necessary to yield 75% correct responses. Error bars show the SEM.

By comparing the motion segmentation and detection curves for both observers (PM and AL), we see that for stimulus durations less than 60–80 msec, the broadest segmentation targets are detected at smaller target speeds than that required to detect motion of a whole field of dots. This is particularly noteworthy because the background in the segmentation stimulus is not static but moves with a speed of 1.6°/sec in the same direction as the target. On the other hand, observers cannot detect a narrow motion segmentation target for any stimulus duration unless they are also able to detect absolute motion of the 6.5° square field. The motion detection curves resemble those for segmentation of the narrowest targets, except that motion detection is not completely saturated after 100 msec. Motion detection thresholds for a broad target (0.72°), measured for observer PM, are slightly higher than for the square field but follow qualitatively the same exponential decline with stimulus duration. (For stimulus duration of 34 msec, the motion detection thresholds for the broad target and square field are $5.96 \pm 0.4$ and $4.6 \pm 0.3$ °/sec, whereas the motion segmentation threshold for the broad target is $2.23 \pm 0.3$ against a background speed of 1.6°/sec.) These results suggest a qualitative difference between the segmentation mechanisms responsible for detection of broad and narrow targets. Segmentation of the broad target saturates more rapidly than does detection of its motion.

The suggestion that a coarse scale segmentation mechanism underlies the rapid detection of the broad target and is distinct from the mechanism underlying detection of the narrow target is bolstered by predictions from probability summation. If the same mechanism operates for both, but simply recruits more signal for the broad target, then the probability of detecting the broad target should be no greater than that of detecting several narrow targets summing to the same area. For stimulus duration of 34 msec, for observer PM, the predicted threshold for the target of width of 0.32° computed by probability summation of two independent responses to targets of width 0.16° is $4.12 \pm 0.19$°/sec compared with the measured value of $2.84 \pm 0.09$°/sec. For observer AL, the predicted threshold for the target of width 0.72° computed by probability summation of four responses to targets of width 0.16° is $5.6 \pm 0.25$°/sec, compared with the measured value of $3.3 \pm 0.11$°/sec. Therefore, detection of the broad target cannot be explained by simple spatial summation of the narrow target detection mechanism.

These results show that motion segmentation depends on spatial as well as temporal scales. One possible explanation for the difference in temporal build-up between broad and narrow targets might be that it is harder to detect movement *per se* of the narrow target. For observer PM in Fig. 3, segmentation thresholds for the narrowest target and motion detection thresholds are similar (about 5°/sec) for the shortest duration of 34 msec. If the difference between narrow and broad targets is caused by difficulties in detecting movement of the narrow target, it should disappear when the speed of the narrow target is well above 5°/sec. We therefore repeated the measurements with a background speed of 4.8°/sec and target speeds larger than 5°/sec. Fig. 4 shows that the difference between the broad and narrow targets persists.

Fig. 5 shows how color segmentation thresholds depend on stimulus duration and target size (experiment IIb). In contrast to motion segmentation, there is no temporal build-up of color segmentation for the durations studied here. Rather, there is a slight tendency for thresholds to increase with stimulus duration (observer GT). For all stimulus durations, broad targets are more easily detected than narrow targets. As for motion segmentation, the color segmentation thresholds for broad targets cannot be predicted by probability summation of segmentation performance for narrow targets summing to the same area. For example, probability summation for the 0.72° target from two 0.32° targets predicts thresholds of 0.390 and
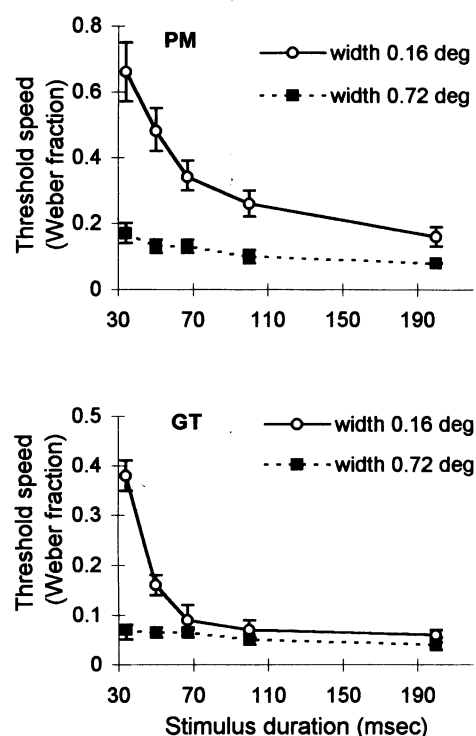


FIG. 4. Temporal build-up curves for motion segmentation of uniform speed distributions for a background dot speed of 4.8°/sec, for two target sizes (observers PM and GT). Thresholds are given as Weber fractions of target-background speed (see Fig. 2) at 75% correct responses. Error bars show the SEM.

0.399 compared with observed thresholds of 0.382 and 0.391 for observers PM and GT, respectively (with SEM values of $\pm 0.002$ for each). Thus, color segmentation depends on spatial, but not temporal scales.

## DISCUSSION

These results reveal two important features of segmentation by motion: thresholds decrease with target size and temporal build-up of the segmentation signal depends on target size. Segmentation by color is qualitatively different: although color segmentation thresholds also decrease with target size, there is no temporal build-up of the segmentation signal for any fixed target size. For both motion and color, the difference in segmentation behavior between broad and narrow targets cannot be explained by an edge-based process: narrow targets with either edge aligned to the corresponding edge of the broad target are less easily detected than the broad target. The lower detection thresholds for the broad target cannot be predicted by probability summation of detection of the two narrow targets combined (with inner and outer edges aligned to the broad target, respectively). Edge-based processes, therefore, cannot be solely responsible; the difference in segmentation behavior of the broad and narrow targets must lie in the operation of region-based processes.

For motion segmentation, this conclusion is further supported by the difference in the temporal build-up functions for broad and narrow targets. The temporal build-up curve rapidly flattens as target size increases. For a given speed difference between target and background, a broad target is detected faster than a narrow target. This result suggests that the region-based process in motion segmentation is fastest or perhaps operative only on a coarse scale.

Comparing these results with the motion detection curve reveals that absolute motion detection cannot underlie this fast region-based segmentation process. For stimulus durations

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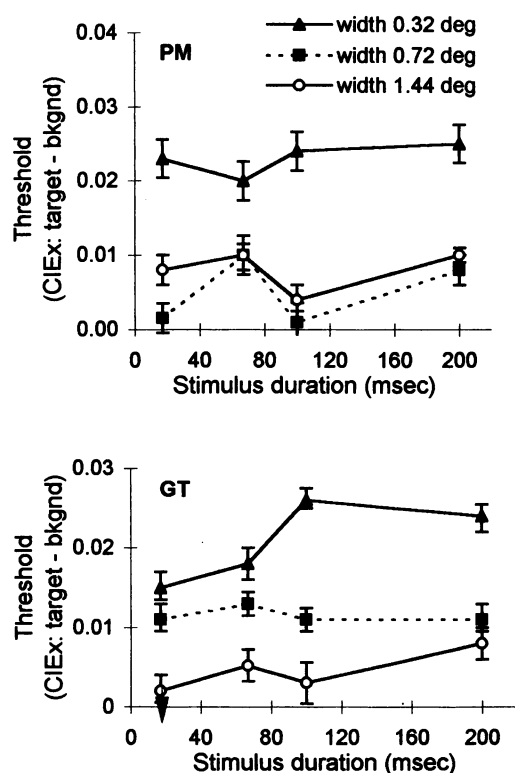*Proc. Natl. Acad. Sci. USA 93 (1996)*     7425

FIG. 5.   Color segmentation thresholds as a function of target size and stimulus duration (observers GT and PM). Thresholds are given as the difference between the mean CIE $x$ values of the target and background distributions at the level of 75% correct responses. Error bars show the SEM. The shortest duration, 17 msec, corresponds to one frame. Downward arrow marks upper limit for threshold.

shorter than 60–80 msec, segmentation thresholds for the broad target are smaller than motion detection thresholds, even when the segmentation threshold is expressed as absolute target dot speed. The data suggest instead that a mechanism that detects relative motion between target and background dots underlies the rapid segmentation of the broad target. In contrast, the temporal build-up curve for the narrow target is steep, resembling more the absolute motion detection curve as well as build-up functions for speed discrimination (23, 24). At every stimulus duration, segmentation thresholds for the narrow target are higher than those for absolute motion detection. But the difference in temporal dependence for broad and narrow targets persists at target speeds well above the threshold for absolute motion detection, showing that it is not caused by difficulty in detecting motion of the narrow target.

These data support the existence of two fundamentally distinct motion mechanisms with distinct spatiotemporal properties: one that signals relative motion between two regions; and another, slower one that signals absolute motion, or rather, motion relative to the observer.*

The relative motion mechanism responds rapidly and with greater sensitivity to small speeds (or speed differences) than the absolute motion mechanism. This conclusion is consistent with Snowden's finding (25) that the minimum displacement limit for motion detection (dmin) in random dot patterns is governed by relative, not absolute, motion signals.

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*We cannot exclude the possibility that detection of the absolute motion stimulus occurs by detection of its motion relative to the monitor frame, which was dimly visible in an otherwise black tunnel. We argue that such motion detection is still qualitatively distinct from detection of relative motion contained in the stimulus because for the short stimulus durations used the monitor frame is a low-contrast peripheral stimulus whose detectability is minimal.

Our results suggest that the relative motion mechanism is responsible for fast region-based segmentation. The most plausible explanation for the robust difference in segmentation behavior for the broad and narrow targets is that this relative motion mechanism is responsible for both, but slower for narrow targets because of its inherent dependence on spatial scale.

The region-based segmentation process must derive from a similarity signal within the target. How might this signal be generated? There are two main possibilities: the first is a simple linear filtering process that adds local motion signals; the second is a cooperative process involving nonlinear interactions between motion signals over space (26, 27). Each would then be followed by a decision process that determines segmentation. The first possibility is unlikely given that segmentation performance for the broad targets cannot be predicted by probability summation of the independent responses to an appropriate number of narrow targets adding up to the same width. Further support for a nonlinear cooperative process lies in the result that segmentation thresholds are nearly the same for broad targets with finite speed distributions that overlap extensively with the background speed distributions as for targets and backgrounds with nonoverlapping uniform speeds. If local feature contrast detection were the only source for motion segmentation, segmentation should become very much harder for overlapping target and background distributions, contrary to what we find. Indeed, for short durations, the overlapping and nonoverlapping speed distributions "look" the same.

It is therefore most likely that the region-based process underlying motion segmentation of the broad target involves fast coherent signals generated by cooperative interactions between local motion signals. Our data suggest that this process integrates information initially over a coarse spatial scale. For the narrow targets, this integration over space is initially dominated by the background signal, and the motion differences are swamped. Thresholds for narrow targets rise steeply for short stimulus durations, but over time the finer-scale discontinuities emerge and thresholds decrease.

Our results are consistent with the conclusion of Vaina and Grzywacz (28) from studies on brain-lesioned patients that the computation of motion coherence, involving spatial integration of motion signals, is distinct from motion discontinuity localization. Vaina and Grzywacz (28) also conclude that the visual system does not need fully encoded velocity signals for motion discontinuity localization, as suggested by Clocksin (29). These results argue against an alternative hypothesis to explain our data that an edge-based process mediates segmentation of the narrow target and requires absolute motion signals to be independently detected within target and background, and then differenced.

Our results also demonstrate an early contribution of region-based processes to segmentation by color. Since the local feature contrast between target and background is minimized by the overlapping color distributions, segmentation requires the integration of signals over space. Clearly these signals increase in strength as the size of the target increases. As was the case for motion, we cannot explain the psychometric functions for a broad target by the independent action of two local border mechanisms. There is a fundamental difference between the segmentation mechanisms for color and motion: the color segmentation signal does not build up with stimulus duration for any target width, whereas the motion segmentation signal does. This difference cannot be because the motion stimulus simply provides more information for segmentation over time, as there is no build up of the color segmentation signal even when all target and background dots are in motion (with either random or uniform speeds) (30).

In summary, we conclude: Region-based segmentation processes make early contributions to segmentation by both motion and color. For motion, the region-based segmentation

process operates from coarse to fine scales, is faster on a coarse scale than an edge-based process, and relies on a relative motion detection mechanism. For color, the region-based process does not integrate over time but strongly depends on spatial scale. Region-based segmentation by color may, therefore, reach completion simultaneously on each of several distinct spatial scales. On the other hand, other results (e.g., refs. 12 and 13) clearly demonstrate the importance of local feature contrast for segmentation in all domains (motion, color, luminance, texture, and disparity). If region-based processes for segmentation exist alongside edge-based processes, surface detection might not necessarily require establishment of local discontinuities. The early visual system might be more interactive and less hierarchical than assumed by standard theories (31, 32).

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