Supplementary Methods

Calibration & gaze quality

A nine-point calibration was performed by asking the subject to look at designated objects in the scene outside the garage. Successful calibration was verified by asking the subject to fixate the same objects again. If the online visualization of gaze position for some calibration points was off (by about two degrees or more), a recalibration was performed. On the road, maintaining calibration was verified by visual judgment between each run, by designating objects for the subject to look at. A gaze quality criterion of 0.2 supplied by the tracker software was used to exclude data before analyses.

Supplementary figure S1

Nine point calibration used to calibrate the eye-tracker. White dots are placed at the designated calibration points. The colored dots represent data-points of gaze position. The red ellipse indicates the approximate part of the visual field where the tangent point falls in during cornering.
Horizontal and vertical, gaze deviation (difference of median observed gaze position from designated target point) is under 2°. Black dots: calibration datapoints from the current dataset. Open red circles: calibration datapoints from another simultaneously collected dataset.

Mathematical description of the segmentation algorithm

The system aims to maximize a fitness function, although it is not known if it actually reaches a (global) maximum:

$$L(S) = \sum_{s \in S} \left( P(s_0, \lambda) + \sum_{i \in S} G(\hat{x}_i - x_i; 0, \Sigma) 1_{i \in O} \right) + \sum_{i \in O} c P(i, \lambda)$$

where $P$ is logarithm of the Poisson survival function for more than zero events with rate parameter $\lambda$ for a new segment with $i$ being time between samples $i$ and $i-1$, $s_0$ denotes the first sample index in the segment, $G$ is logarithm of the Gaussian probability density function with mean zero and (diagonal) covariance matrix $\Sigma$, $O$ is the set of outliers and $c$ is a
“penalty coefficient” for outliers, is the signal value of sample and is its estimate based on the segment's linear fit.

For the present analyses we used $\beta = 1/0.5$ and $\gamma = 0.6$ based on tuning by hand. was iteratively estimated similarly to the Expectation Maximization method by calculating the ML estimate based on a run of the algorithm and then running it again with the new estimate until the segmentation does not change. We used initial noise variances of 1.0 for both dimensions.

Supplementary Results

Driving behavior

The following figures and tables quantify physically driving behavior in the cornering phase in the present study. The Supplementary Figure S3 and S4 display group level and individual driving speeds as a function of lap. Supplementary Tables T1 and T2 show individual participants' yaw-rate and the eccentricity in the visual scene.

SUPPLEMENTARY FIGURE S3

Boxplot showing average driving speed in the cornering phase as a function of lap.
**SUPPLEMENTARY TABLE ST1**

*Per subject vehicle yaw rate in the cornering phase (Mean, SD)*

| Participant | Yaw-dot M | Yaw-dot SD |
|-------------|-----------|------------|
| 1           | 13.5      | 1.2        |
| 2           | 14.6      | 0.9        |
| 3           | 13.5      | 1.2        |
| 5           | 12.9      | 0.9        |
| 6           | 12.8      | 1.3        |
| 7           | 13.6      | 1.5        |
| 10          | 12.9      | 1.1        |
| 11          | 13.9      | 1.1        |
| 12          | 14.2      | 1.2        |
| 13          | 14.0      | 0.9        |
| 14          | 14.1      | 1.0        |
| 15          | 13.9      | 0.9        |
| 16          | 13.6      | 1.0        |
| 17          | 14.6      | 1.3        |
| 18          | 16.2      | 1.7        |
| 19          | 13.0      | 0.8        |
| 21          | 14.7      | 1.5        |

**SUPPLEMENTARY TABLE ST2**

*Horizontal angle of TP in vehicle centered coordinates during cornering (Mean, SD).*

| Participant | TP° M | TP° SD |
|-------------|-------|--------|
| 1           | 16.7  | 1.4    |
| 2           | 18.3  | 1.1    |
| 3           | 19.5  | 1.3    |
| 5           | 19.4  | 1.2    |
| 6           | 19.4  | 1.0    |
| 7           | 18.4  | 1.7    |
| 10          | 18.0  | 1.2    |
| 11          | 18.9  | 1.2    |
| 12          | 16.1  | 1.5    |
| 13          | 16.6  | 1.1    |
| 14          | 17.8  | 1.0    |
| 15          | 17.7  | 1.2    |
| 16          | 16.9  | 1.5    |
| 17          | 14.1  | 1.6    |
| 18          | 16.1  | 1.6    |
| 19          | 15.1  | 1.7    |
| 21          | 17.0  | 2.7    |
Supplementary Figure S4

Density distribution of gaze displacement from the tangent point, with marginal distributions. The shaded areas represent highest-density regions with 75%, 50% and 25% thresholds. Individual subjects’ data.
Supplementary Figure S5

Histograms of the direction of each participants’ pursuit eye movements.
Density distribution (in velocity-velocity phase space) of horizontal and vertical gaze velocity. The shaded areas represent highest-density regions with 75%, 50% and 25% thresholds. Individual subjects data.
Supplementary Discussion

In this appendix to the discussion on the different models, we outline the different alternative predictions open to TP and FP models concerning gaze position and eye-movements (changes in gaze position). The derivations are explained in more detail here because, given that OKN was only recently demonstrated, most of the models do not discuss it explicitly. Especially reasoning out behind how OKN SP and QP “should” behave when the tangent point is being tracked is tricky because by the qualitative nature of the models and parameters of eye movement behavior cannot be derived quantitatively.

**Tangent point models** a postulate that

1. tangent point orientation results from a visual strategy where drivers track the tangent point, (rather than contiguous points on the future path)
2. the tangent point is tracked because it provides preview information of road geometry relevant to adjusting steering

**Future path models** posit that:

1. a target point on the future path is tracked because it provides preview information of road geometry relevant to adjusting steering
2. tangent point orientation is mainly a result of contiguity of the future path reference point(s) and the tangent point.

Assumptions of exact gaze target combined with known properties of optical flow and the assumption that optokinetic pursuit follows regional optic flow regardless of which target point is being visually tracked point to new ways of assessing the tangent point and the future path as drivers’ gaze target in.
OKN & tangent point models

TP Hypothesis 0. The default prediction from targeting the TP would be that fixation is stable at the TP, and the flow pattern around the tangent point would not affect the rotation of the eye. It is currently not known from experiment whether it is possible for human subjects to suppress OKN while looking at the TP.

TP Hypothesis 0 (no OKN). Persistent fixation of the tangent point. Gaze is stable at the TP. Possibly observed in the TANG condition in Kandil et al. (2009) – although the presence or absence of OKN was not analysed in that study – but not in everyday driving.

That OKN is reliably elicited, however, shows that either the OKR is present while the TP is fixated (or that the drivers are not looking at the TP).

If the drivers’ “attemp” to fixate the tangent point is hindered by OKR elicited by regional flow, gaze would move away from the fixation target and require re-setting saccades to restore fixation (hence OKN QP). QP characteristics may be therefore predicted if the dependence of SP on regional flow is known.

TP Hypothesis 1. Under the assumption that the OKR follows local flow, QP could re-set gaze to the tangent point (assuming the SP has drawn gaze away from it), or to launch gaze “upstream” in the flow field, so that the slow phase pursuit OKR will bring gaze back to the TP.
Because the tangent point falls on the line of inversion (zero crossing) of the horizontal component of optic flow, the flow at the tangent point is vertical (downwards). The simplest prediction would then be that the SP pursuit movements follow the local flow at the point of regard which, with perfect TP fixation and the vertical local flow at the tangent point would mean a vertical downward SP, and a vertical upward QP.

**TP Hypothesis 1. OKN SP following local flow at the TP (vertical), with re-setting QP. A pattern not observed in the present study or Authié & Mestre (2011).**

A vertical OKN is not, however, what is observed. Neither in the present study nor in Authié & Mestre (2011) study. Instead, a large horizontal component against the direction of the curve is observed. Therefore is must be concluded that either gaze does not follow local flow, or else drivers do not fixate the tangent point, but a point on the road beyond (where the flow does have a large horizontal component).

**TP Hypothesis 2. If gaze is targeted at the tangent point, but is not stable at the tangent point because of OKR. But the as the SP does not follow local flow (it has a horizontal componens) the hypothesis needs to be adjusted.**

The dependency of OKN SP on regional optic flow is not clear, and the assumptions of the TP hypotheses (above) do not give a specific prediction. Empirically, it is known that it is opposite to the direction of the curve and downwards. Thus,
although local flow at TP is downwards, the OKR would be affected by regional flow elsewhere, in particular above the TP:

TP Hypothesis 2. Optic flow “captures” gaze. The direction of OKN SP does not follow local flow at TP, but flow of some region around the TP. This region needs to be determined to predict OKN behavior quantitatively. Empirically, it is known that the SP in fact takes gaze downwards and to the left.

TP Hypothesis 3. Another possibility would be to launch gaze “upstream” in the flow field, so that the slow phase pursuit OKR will bring gaze back to the TP:

TP Hypothesis 3. Gaze is cast “upstream” in the flow field. OKN following (regional) optic flow re-sets gaze to tangent point.

There are thus many ways in which targeting the TP and OKN could be combined. Unless the size and shape of the relevant region assumed to determine the OKN SP need to be incorporated SP direction and magnitude is underspecified.
OKN & future path models

If a point on the future path is tracked the slow phase component of OKN should track a fixed target location. QP’s are saccades to a new target location.

**FP Hypothesis 0.** Tracking a fixed location does not necessarily lead to OKN. If the location is tracked for several seconds (as in the “gaze sampling” condition in Kandil et al. 2009), a visual sweep is performed instead:

*FP Hypothesis 0 (no OKN). Visual sweep of a future path target point. This gaze behavior was given as an instruction in an experimental manipulation by Kandil et al. (2009), but is not observed in normal driving.*

The future path presents no immediately apparent singular reference point, and to determine OKN a model needs to specify where on the FP gaze is expected to land (the regional flow on the FP is not the same everywhere)
**FP Hypothesis 1.** In Boer’s (1996) model, the target is selected adjacent to the tangent point:

![Diagram of FP Hypothesis 1](image)

**FP Hypothesis 1.** Target point next to the tangent point is selected and tracked by a pursuit movement.

**FP Hypothesis 2.** We favor a hypothesis where a reference point in the Far Zone beyond the tangent point is used:

![Diagram of FP Hypothesis 2](image)

**FP Hypothesis 2.** OKN in the Far Zone beyond the tangent point.

**FP Hypothesis 3.** The two FP hypotheses can be integrated into a gaze polling model:

![Diagram of FP Hypothesis 3](image)

**FP Hypothesis 3.** Gaze polling in the far zone. Cf. Figure 1, middle, in main article.
