

METHOD FOR EXTENDED FIELD-OF-VIEW ANGLE MEASUREMENT BASED ON CHAIN TRACKING OF FEATURE POINTS

Guo Qicheng

Belarusian State University of Informatics and Radioelectronics

E-mail: 2733064287@qq.com

Summary. In visual navigation and positioning tasks, agents often fail to simultaneously observe two distant feature points due to the limited field of view (FOV) of the camera, leading to angle measurement failure. This paper proposes a chain tracking measurement method, this method does not rely on additional hardware, utilizing only natural feature points in the image sequence for chain tracking and angle accumulation, making it suitable for resource-constrained mobile agent platforms. Experimental results demonstrate that the method effectively overcomes physical FOV limitations, enhancing the flexibility and robustness of angle measurement.

1. Introduction.

In visual positioning systems for mobile agents such as robots and UAVs, the limited camera FOV often prevents the simultaneous observation of two distant target points. For instance, in the scenario shown in figure 1, when agent B is observing, the angle between points A and C may far exceed the camera's FOV, making it impossible to co-visualize them in a single frame. Traditional methods typically rely on multi-camera systems or wide-angle lenses, but this increases system cost and complexity [1].

To address this issue, we propose a feature point chain tracking measurement method. This paper details the workflow, mathematical model, and application potential of this method in visual navigation.

2. Method.

When the angle subtended by points A and C at agent B is very large, exceeding the camera's FOV, they cannot be observed simultaneously. To address this, we propose the chain tracking measurement scheme (as shown in figure 1).

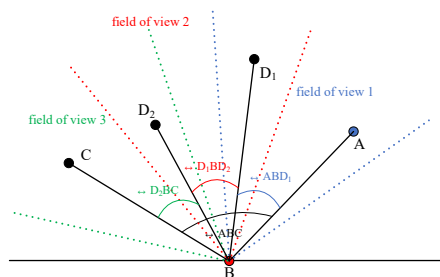


Figure 1 – Feature Point Chain Tracking Measurement Model

Agent B begins to rotate. When A moves to the left edge of its FOV (a preset threshold), if C has not yet appeared, a stable, easily trackable natural feature point D_1 is sought near the right edge of the FOV.

Record the horizontal pixel coordinates u_A and u_{D_1} of A and D_1 at this moment, and calculate and store the angle $\angle ABD_1$:

$$\angle ABD_1 = |u_{D_1} - u_A| * \theta_{pixel} . \quad (1)$$

Agent B continues rotating, using D_1 as the new reference. When D_1 moves to the left edge of the FOV , if C still has not appeared, similarly seek the next stable, easily trackable natural feature point D_2 near the right edge.

Record the horizontal pixel coordinates u_{D_1} and u_{D_2} of D_1 and D_2 at this moment, and calculate and store $\angle D_1BD_2$:

$$\angle D_1BD_2 = |u_{D_1} - u_{D_2}| * \theta_{pixel} . \quad (2)$$

Repeat this process until the target C appears within the FOV . Record the pixel coordinates of the last feature point D_i and C , and calculate $\angle D_iBC$:

$$\angle D_iBC = |u_C - u_{D_i}| * \theta_{pixel} . \quad (3)$$

Finally, $\angle ABC$ is the algebraic sum of all intermediate angles:

$$\angle ABC = \angle ABD_1 + \angle ABD_2 + \dots + \angle D_iBC . \quad (4)$$

This method effectively extends the virtual FOV by introducing a series of intermediate natural feature points as “angle beacons”, overcoming the limitations of the physical FOV .

3. Experiments and Results.

We conducted verification experiments using a camera with a horizontal resolution of 4032 pixels, a horizontal focal length of 3063.14, and a horizontal FOV of 69.4883° . The results under various angles are shown in table 1.

Table 1 – Experimental results

True value ($^\circ$)	Measured value ($^\circ$)	Error value ($^\circ$)	Error rate (%)
75	72.88	2.12	2.83
90	89.03	0.97	1.08
105	106.71	1.71	1.63
120	124.41	4.41	3.68
135	136.18	1.18	0.87
150	151.33	1.33	0.89
165	168.48	3.48	2.11

The results indicate that the method maintains small errors across different angles, making it suitable for most visual navigation scenarios.

4. Conclusion.

This paper proposed a method for extended FOV angle measurement based on chain tracking of feature points. By dynamically selecting intermediate feature points and progressively transferring angles, it effectively overcomes the

limitations of the camera's physical *FOV*. The method requires no additional hardware, is applicable to monocular vision systems, and possesses strong practicality and scalability.

References

1. A Review on Challenges of Autonomous Mobile Robot and Sensor Fusion Methods / M. B. Alatise, G. P. Hancke // IEEE Access. – 2020. – Vol. 8. – P. 39830–39846.

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INTELLIGENT TRADING FRAMEWORK BASED ON LARGE LANGUAGE MODELS

Guo Yu

Belarusian State University of Informatics and Radioelectronics

E-mail: 305619456@qq.com

Summary. *This paper presents an intelligent trading framework based on large language models. This system integrates the semantic reasoning of LLMs with classic statistical models, using LLMs to analyze news, sentiment, and macro reports to generate signals. These signals are combined with historical data and then drive the risk control module. The trading system replaces human analysts, providing 24-hour automated monitoring, reducing the working hours of human analysts, and promptly capturing event-driven opportunities during market fluctuations.*

Algorithm-based quantitative trading systems dominate mature financial markets. Large language models (LLMs), such as the GPT series, can be used to deeply understand the semantic information hidden in news texts, company announcements, and macroeconomic policies [1]. These superior LLMs possess strong capabilities in logical reasoning, information extraction, and sentiment analysis. We can train LLMs to interpret the “hawkish” tone of Federal Reserve meetings or infer a company's future profit potential from its financial reports [2]. This enables the automatic generation of alpha signals based on financial semantic recognition.

We have designed a hybrid intelligent trading system that integrates LLM with classic quantitative models. In this system, LLM serves as an information processor and signal enhancer, and then this automated processor is incorporated into traditional quantitative models.

The system's three-layer architecture: information perception layer, signal fusion layer and transaction execution layer.

1. Information Perception and Processing Layer: Responsible for real-time acquisition and extraction of information from multiple heterogeneous data sources.

Data Sources: mainstream financial news media, company official announcements, selected financial opinions on social media platforms, macroeconomic data reports.