Social Doppler: A Framework for Mechatronic Perception Beyond Physical Radar

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***Abstract*—In traditional embedded mechatronic systems, sensors are mainly focused on capturing the geometric and dynamic states of the physical world. However, in typical Cyber Physical Social Systems scenarios such as urban transportation and service robotics, physical sensing alone is not sufficient to capture shifts in public attention, emotional changes, and the evolution of public opinion. This paper proposes a Social Radar Doppler perception framework designed for embedded systems. By drawing an analogy with the classical Doppler effect in radar systems, the framework establishes a quantifiable model for the speed, direction, and dynamic features of social emotions and topics. In addition, we introduce a closed-loop 6S embedded social radar perception architecture. This architecture includes modules for data acquisition, semantic integration, emotion tracking, and strategy feedback. This framework can be broadly applied to support early decision-making in socially intelligent agents and provides a new perceptual dimension for future systems that deeply integrate humans, machines, and society.**

***Index Terms*—Social radar, Doppler effect, affective computing, Agentic AI, collective Intelligence.**

I. Introduction

In recent decades, embedded sensing and mechatronics have rapidly advanced autonomous systems across intelligent transportation [1], autonomous driving [2], robotics [3], and smart manufacturing [4], among others [5]. Traditional approaches rely on high-precision modeling and sensing of the physical environment, commonly using millimeter-wave radar [6], LiDAR [7], and vision systems [8] to capture position, velocity, and acceleration. However, as applications extend to complex social contexts—such as passenger emotion recognition, public-sentiment monitoring for urban governance, and opinion tracking in disaster response [9]—reliance on purely physical modalities becomes insufficient. There is an urgent need to model and understand collective behavior, group emotions, and the evolving dynamics of public attention [10], [11], [12], [13].

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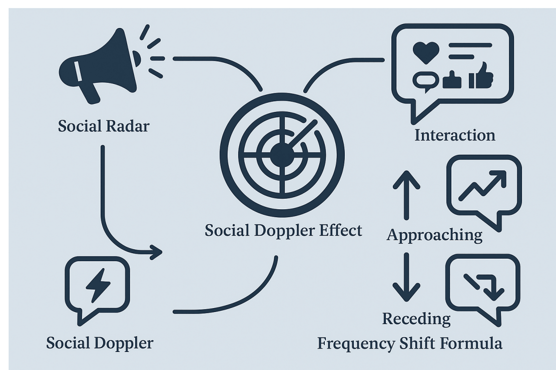

Fig. 1. Conceptual diagram of the social radar doppler effect

Drawing on Harold D. Lasswell's idea of environmental surveillance[14], Wilbur Schramm introduced "social radar"[15], a process akin to radar that collects and processes information to help people detect changes in internal and external environments and adjust their behavior. In the 2010 Arab Spring, social media played a central role in mobilization, leading to widespread violence with major social and economic consequences[16]. This episode brought "social radar" back into view as a service platform based on social networks and social media.

Recent research has begun exploring the integration of ”soft variables”—such as language, emotion, and group behavior—into the perception chain of embedded systems, aiming to support a new generation of intelligent systems within Cyber–Physical–Social Systems (CPSS)[17], [18]. Driven by Agentic AI[19], agents are capable of not only autonomous perception and decision-making, but also collaborating across multiple agents to form collective intelligence[20], enabling distributed perception and response to complex social dynamics. However, these socially-aware perception processes often lack a unified engineering framework and standardized metrics. They typically rely on customized natural language processing (NLP) or sentiment analysis tools, making it difficult to establish a spatiotemporal-velocity structure comparable to that of physical sensing[21]. At the same time, feedback and response mechanisms in engineering applications—such as policy dissemination, content scheduling, or path planning—struggle to efficiently couple with the dynamic nature of social signals. In our previous work, we utilized "Social Radar" [22][23] and "Social Voice" [24] to perceive social sentiment and public opinion dynamics. Concurrently, we proposed the integration of Social Radar with Social Vision to construct a "6S" system for the low-altitude economy , which has preliminarily verified its feasibility within CPSS. However, the absence of quantitative and dynamic modeling of social variables (notably emotion) still limits precise behavior sensing and evolution prediction.

To bridge this gap, we introduce a Social Doppler framework inspired by the classical Doppler effect in radar systems [25], [26]. This approach dynamically maps the evolution of social variables into measurable "frequency shift" and "semantic velocity" signals (Fig. 1), enabling real-time tracking and predictive analysis of social opinion targets. The framework establishes a comprehensive system-level mapping between physical radar operations and social perception mechanisms. It introduces a unified measurement scheme based on frequency shift, rate of change, and semantic phase, thereby providing embedded systems with an efficient engineering-oriented method to capture and interpret public attention flow and collective intelligence-driven dynamics.

To implement this, we develop a closed-loop 6S Embedded Social Radar System with six components: Sensing, Semantic Alignment, Social Velocity Estimation, Signal Fusion, Situation Tracking, and Strategic Response. This scalable architecture suits practical deployment. Its effectiveness is shown in real applications such as early public sentiment warnings in transport policy, brand trust erosion detection, and risk propagation modeling in emergencies.

In summary, Social Doppler, grounded in physical analogy and engineering feasibility, offers a promising perception paradigm for next-generation embedded systems in tightly coupled human–machine–society environments. The paper is organized as follows: Section II reviews the classical Doppler effect and social analogy; Section III presents system mapping and measurement; Section IV details the 6S perception process and algorithms; Section V shows three application cases; Section VI discusses challenges and future directions.

II. Mapping Analysis Between Physical Radar and Social Radar

A. Doppler Effect Principle

The Doppler effect is a fundamental phenomenon in classical wave propagation physics, referring to the frequency shift observed when there is relative motion between a wave source and an observer. In radar systems, the radial velocity v_r of a target induces a frequency shift f_D in the received echo signal.It can be calculated using the following formula:

$$f_D = \frac{2v_r}{\lambda} \tag{1}$$

where λ denotes the carrier wavelength. This frequency shift is not only used to estimate whether a target is approaching or receding, but also serves as a key principle in target detection, tracking, and prediction, making it a core physical foundation of radar sensing systems.

B. Social Doppler Concept

Based on the analogy with traditional radar, we propose the concept of "Social Doppler" as a novel mechanism for perceiving the dynamics of social information. The core idea is to treat non-physical variables such as "public sentiment," "topic popularity," and "support level changes" as time-varying "social targets," assigning them physical analogues such as velocity and direction.

To be specific, the rate of change of an emotional variable or support function $S(t)$ along the time axis, denoted as $v_s = \frac{dS}{dt}$, is regarded as a "social velocity" metric. This metric can describe whether a topic is rapidly capturing public attention (positive velocity) or gradually fading from the social spotlight (negative velocity). Similar to the physical radar phenomenon where a target causes an increase in frequency, in social systems, when public attention quickly focuses on an event, posting frequency, repost density, and sentiment intensity tend to exhibit "peak clustering," forming a perceivable effect of "social frequency shift."

C. Explanation and Calculation Method of the "Social Doppler Frequency Shift" Indicator

In this study, we further propose a testable modeling hypothesis by introducing a normalized social Doppler frequency shift metric $f_{d,s}$, which quantifies the relative speed of change of social variables with respect to their baseline activity levels. This metric is defined as follows:

$$f_{d,s} = \frac{\frac{\Delta S}{\Delta t}}{f_0} = \frac{v_s}{f_0} \tag{2}$$

where $\Delta S/\Delta t$ denotes the rate of change of sentiment intensity or opinion support per unit time, and f_0 represents the fundamental frequency of the topic or keyword on the observation platform. This dimensionless ratio enables unified comparison across platforms and topics; the approach remains conceptual and needs large-scale validation.

D. Correspondence Analysis Between Radar and Social Radar

To establish the foundation of the Social Doppler framework, we map key stages of traditional radar to social sensing, as shown in Fig. 2. Waveform design, beam steering,

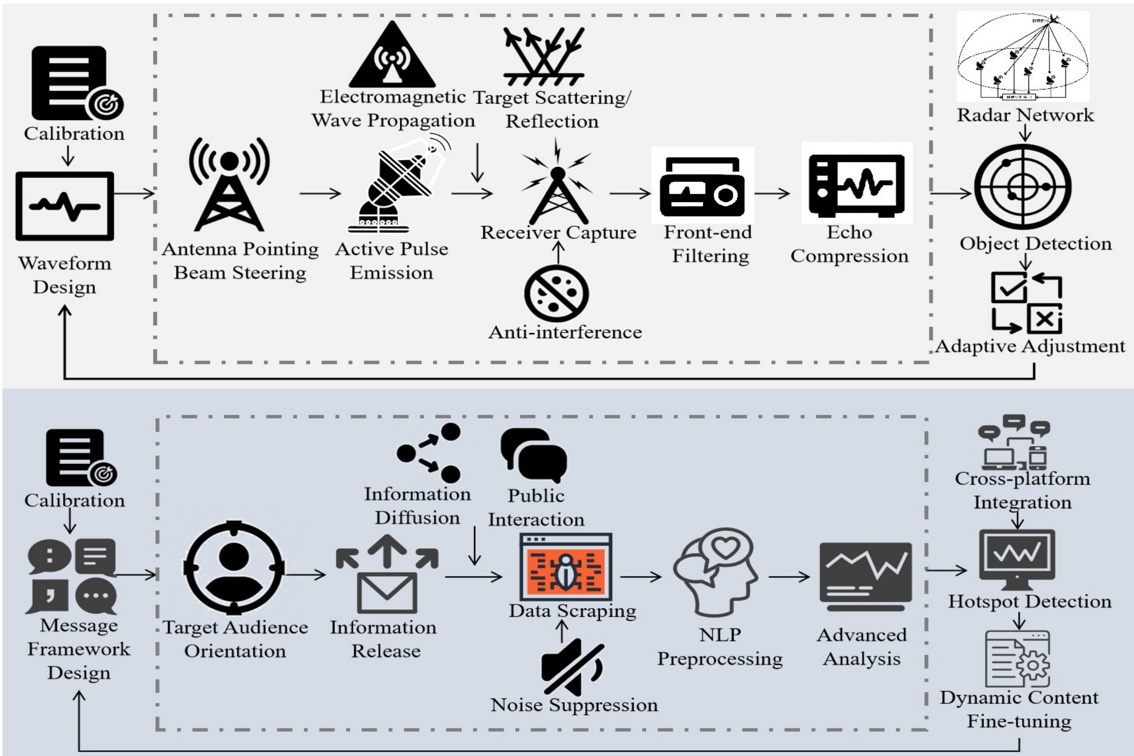

Fig. 2. Structural Mapping Between Radar and Social Radar Systems. This comparison illustrates the correspondence between the signal processing workflow of traditional radar and the information perception stages of social radar.

and pulse emission correspond to message framing, audience targeting, and content release. Electromagnetic propagation and echo reception parallel information diffusion and public interaction; signal processing such as filtering, spectral estimation, and tracking is mapped to NLP preprocessing, sentiment analysis, and topic evolution. Advanced radar functions like anti-jamming, calibration, and adaptation also have clear counterparts, including bot filtering, bias correction, and content adjustment. These parallels form a perception–processing–response loop, offering a structured path for implementing Social Doppler Radar in systems.

Preliminary validation.: As proof of concept, we conducted a small pilot on social media data related to the Russia–Ukraine conflict. Following the pipeline in Fig. 2, we derived sentiment intensity $S(t)$, computed social velocity v_s, and normalized it into $f_{d,s}$. The pilot showed that fluctuations in $f_{d,s}$ often appeared earlier than visible surges in posting volume or raw sentiment, and change-point analysis suggested that its inflection points tended to precede those of $S(t)$. These observations provide preliminary evidence that the proposed indicator can enhance early detection of social dynamics,supporting the practicality of Social Radar.

III. Cross-Domain Fusion Framework: Design of the 6S Embedded Social Radar Perception Closed-Loop System

To enable the deployment of Social Doppler Radar in embedded systems, this paper proposes a 6S closed-loop perception system based on an edge–cloud–device collaborative architecture. Targeting typical Cyber-Physical-Social scenarios, the system integrates social signal acquisition, emotional and semantic modeling, multimodal data fusion, and strategy-driven feedback. It ensures real-time responsiveness and resource control while enhancing cross-platform data interpretability and operability through AI agents. The 6S model covers the full pipeline from signal sampling to feedback execution, forming a closed-loop chain from multi-source information to structured cognition.

A. System Architecture Overview: Perception Chain from Cloud to Edge to End

This system adopts an integrated cloud–edge–end architecture to support flexible deployment and rapid response in large-scale social radar perception tasks, as illustrated in Fig. 3. Specifically, the cloud layer handles cross-platform data aggregation and advanced analytics, including NLP parsing, multimodal fusion, and trend modeling. The edge layer performs local preprocessing and frequency shift estimation, enabling emotional velocity calculation and anomaly screening. The embedded layer is integrated into terminal devices such as service robots and intelligent cockpits, executing tasks like event recognition, content broadcasting, and path adjustment. Together, these three layers form a closed-loop perception chain from global modeling to local response, significantly enhancing system performance in terms of bandwidth efficiency, responsiveness, and interpretability.

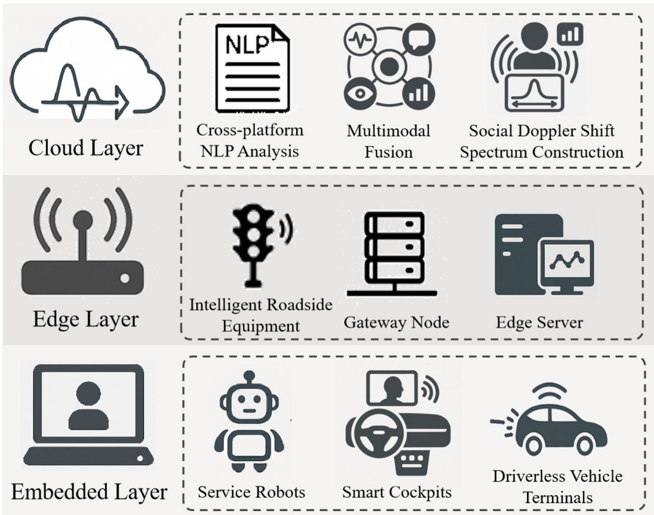

Fig. 3. Three-layer cloud–edge–embedded architecture of the social radar doppler system.

B. 6S Embedded Social Radar Perception Closed-Loop System

The 6S closed-loop system integrates cross-domain data and cognitive feedback through six modules: Source, Sensing, Screening, Semantic Fusion, Situation Inference and Strategic Feedback, ensuring timely, robust and adaptive processing from acquisition to reasoning to action and equipping CPSS embedded systems with social perception.

1) Source: The system begins by collecting heterogeneous, multimodal data—text, images, audio, geolocation, and time—from diverse sources such as social media, news, IoT devices, and sensors. High-concurrency methods like APIs, crawlers, and MQTT streams ensure wide coverage and responsive sampling. The sensing module then normalizes formats, cleans data, and extracts unified feature representations to support downstream fusion.

2) Sensing: At this stage, incoming data is standardized, cleaned, and structured to create stable and reliable feature input streams. Text undergoes deduplication, tokenization, spell correction, and sentiment tagging; audio and images extract spectrogram, visual, or expression features; geographic and temporal data are normalized. Unified vector representations (e.g., BERT, CLIP, MFCC) are then generated, forming a shared feature space that greatly improves the efficiency and overall consistency of subsequent fusion.

3) Screening: To enhance system robustness, preprocessed data is further refined through noise filtering and quality assessment. Redundancy detection and clustering-based deduplication remove duplicate content, while credibility modeling—based on user activity, historical behavior, and account reputation—identifies bot accounts and unreliable sources. Anomaly detection algorithms such as Isolation Forest, Local Outlier Factor (LOF), and adversarial autoencoders filter out low-quality or anomalous data points, preventing downstream contamination. This stage ensures that only high-confidence, high-value information proceeds to subsequent modules.

4) Semantic Fusion: The fusion module integrates data from different sources and modalities into a unified semantic space. Depending on data flow, it applies early, feature, or model fusion to enhance complementarity and consistency, and may use graph embeddings or contrastive learning to add context and structure. The fused representation supports joint modeling of topic evolution, stance, and multimodal emotions, serving as the key layer for subsequent situation recognition and prediction.

5) Situation Inference: After generating fused representations, the system proceeds to high-level semantic modeling and trend prediction. It uses techniques like graph neural networks, sequence modeling, and multi-scale sliding window analysis to track group behavior dynamics, detect emotional inflection points in topic lifecycles, and identify emerging risk zones. This stage transforms raw data into structured social states, serving as the core mechanism for extracting actionable knowledge.

6) Strategic Feedback: Finally, the system conducts intelligent feedback and decision-making based on situation inference, closing the loop from knowledge to action. Feedback occurs at multiple levels: adjusting sampling and source priorities at the data layer, triggering model updates and labeling at the algorithm layer, and issuing early warnings, alerts, prompts, or strategy changes at the application layer. This ensures adaptability and controllable scheduling, supporting real-time iteration from perception to response. The closed-loop design continuously improves the perception–decision pipeline, enhancing responsiveness and efficiency in dynamic social environments.

The 6S model is modular and highly scalable, making it suitable for deployment in embedded systems across different resource-constrained environments.

IV. Application Scenarios Outlook

In CPSS environments where the physical world and social dynamics are closely linked, embedded systems are evolving from traditional geometric sensing to higher-dimensional perception of emotions, public opinion, and behavior trends. The "Social Radar Doppler" models social information dynamics by simulating the physical Doppler effect, providing theoretical and engineering support for this shift. It can be embedded in various applications—such as service robots, vehicle-road systems, and opinion monitoring platforms—working together to form a low-latency "perception–understanding–feedback" loop. The following discusses its embedded deployment prospects and value in intelligent city governance and social intelligence through three typical scenarios.

A. Negative Public Opinion Sudden Change Perception and Automated Intervention in Brand Crises

In the brand crisis management scenario, reviews from multiple platforms are aggregated at the cloud layer and the

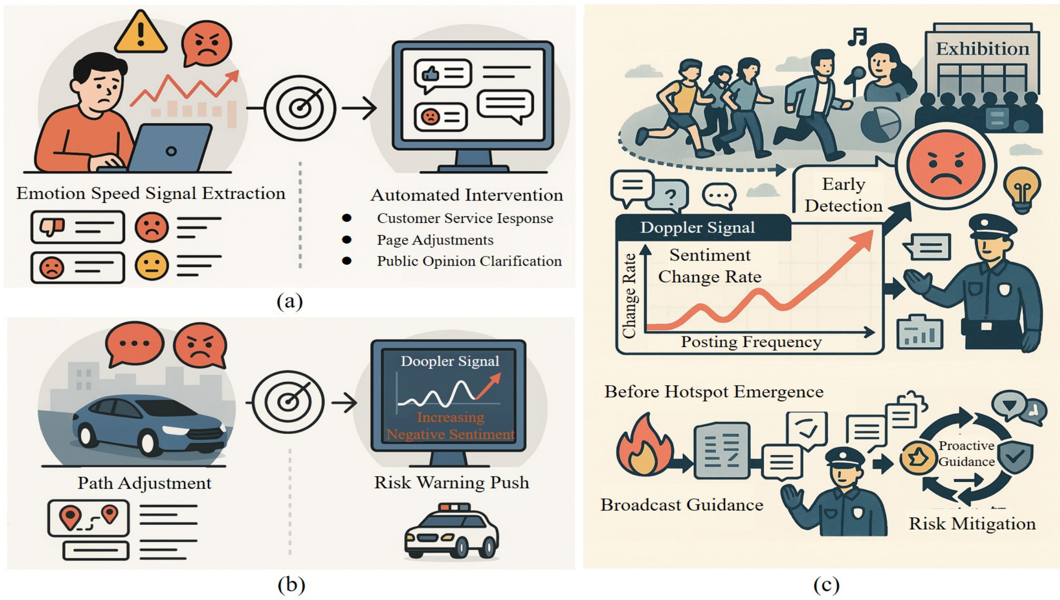

Fig. 4. Application Framework and Response Mechanisms of the Social Radar Doppler in Three Representative Scenarios:(a) Brand Crisis Management, (b) Situation Awareness in Intelligent Vehicle–Road Collaboration, (c) Public Opinion Risk Early Warning during Large-Scale Urban Events

social Doppler frequency shift is calculated. The edge layer is responsible for anomaly screening and fake information detection, while the embedded layer, integrated into website back-end systems, executes page adjustments and customer service responses. Within the 6S framework, “Source” corresponds to opinion data acquisition channels, “Semantic Fusion” integrates textual reviews with public interaction data, and “Strategic Feedback” is realized through automated clarification messages and customer service interventions, forming a closed-loop process from perception to response.

B. Social Risk Situation Prediction and Response in Intelligent Vehicle-Road Collaborative Systems

In the intelligent vehicle–road collaboration scenario, traffic-related opinion data from multiple platforms are integrated at the cloud layer and the Doppler shift indicator is calculated. The edge layer, deployed in roadside units, performs local detection and preprocessing, while the embedded layer in vehicles provides voice broadcasting and route adjustments. In the 6S process, “Source” supplies traffic-related social data, “Screening” removes redundant and false signals, “Situation Inference” predicts the propagation of risks, and “Strategic Feedback” is implemented through navigation optimization and broadcasting, thereby linking social perception with physical modeling.

C. Public Opinion Risk Prediction and Response in Large City Events

In the large-scale city event scenario, cross-platform emotional signals are monitored at the cloud layer and modeled for trend analysis. The edge layer combines crowd sensor data with online opinion streams for real-time processing, while the embedded layer executes broadcasting and evacuation guidance. In the 6S framework, “Sensing” corresponds to the joint acquisition of crowd density and social signals, “Semantic Fusion” aligns multimodal data into a unified representation, and “Strategic Feedback” is carried out through broadcast interventions and safety guidance, enabling early warning and proactive intervention prior to emotional outbreaks.

Fig. 4 demonstrates the application framework and response mechanism of the ”Social Radar Doppler” in three typical scenarios: (a) In brand crisis management, the system captures signals of negative emotional fluctuations, triggering customer service responses, page adjustments, and the release of clarifying information to construct a closed-loop intervention mechanism. (b) In intelligent vehicle-road collaboration, the system perceives the trend of emotional spread related to traffic, linking with route planning, voice broadcasting, and risk alerts, enabling rapid perception of ”social disturbances” and multimodal responses, thereby enhancing the safety and resilience of the transportation system. (c) In large-scale city events, the system proactively identifies potential public opinion risks by detecting the rate of emotional change, linking with broadcast guidance and security interventions to achieve early warning.

V. Conclusion

This paper proposes a “Social Radar Doppler” perception framework, grounded in the classical Doppler effect in physical radar systems, to address real-time sensing and responsive decision-making challenges in dynamic social opinion environments within embedded CPSS systems. By transferring frequency shift modeling into a social context, the framework introduces a normalized index system for quantifying emotional fluctuations and topic evolution, and designs a closed-loop system with the 6S process and AI feedback module. It simulates the full chain of "transmission–diffusion–echo–reception–processing," enabling social signals to have measurable "velocity" attributes. This shifts public opinion response from experience-driven to second-level sensing and predictive recognition, supporting urban governance and brand security.

In terms of innovation, the "Social Radar Doppler" framework proposes novel metrics such as "emotional velocity" and "frequency shift bandwidth," and builds a 6S integrated perception loop based on CPSS theory, covering data acquisition, denoising, semantic fusion, situation inference, and strategic feedback. By integrating large language models and reinforcement learning, the system not only gains semantic understanding but also generates adaptive strategies, evolving from a "perception tool" to a "cognitive engine." This paradigm expands Doppler principle applications into social spaces, offering theoretical and practical support for next-generation human–machine–society coupled systems.

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