TABLE III. ABLATION STUDIES WITH E=5, R=20, M=3, 5 AND 9 (BATCH SIZE = 8 WHEN M=9, WHILE BATCH SIZE = 32 WHEN M={3,5}).

Model Setting	Precision			Recall			F1-Score		
	M=3	*M=5*	*M=9*	*M=3*	*M=5*	*M=9*	*M=3*	*M=5*	*M=9*
FedRME w/o FLO	66.901%	55.937%	55.269%	47.218%	41.829%	35.008%	55.362%	47.866%	42.865%
FedRME w/o WC	67.736%	58.049%	54.081%	43.915%	41.946%	33.522%	53.284%	48.700%	41.389%
FedRME	**72.262%**	**58.603%**	**55.912%**	**50.219%**	**43.035%**	**37.049%**	**59.257%**	**49.627%**	**44.565%**

TABLE IV. COMPUTATION COST COMPARISON OF DIFFERENT METHODS WITH IOU THRESHOLD=0.8, M=3, 5 AND 9.

Methods	FedAvg	FedRME w/o FLO	FedRME w/o WC	FedRME
M=3	8	8	9	6
M=5	11	12	10	12
M=9	14	14	13	13

V. CONCLUSION

In this paper, we present *FedRME*, a novel federated road markings extraction system to collaboratively learn a global RME model without sharing sensitive 3D point clouds data. To address the data heterogeneity among clients, we adopt the classical FedAvg model to construct a generalizable global feature embedding model without accessing local data. For cooperative optimizations in clients, we design a dynamic weighting mechanism to enhance the cooperative training effectiveness before server aggregation. Extensive empirical studies on three real-world mobile LiDAR point clouds datasets demonstrate that FedRME effectively elevates performance and reduces computation by up to 25%. In the future, we plan to: 1) consider the system heterogeneity among clients, such as user dropouts; and 2) deploy the federated system on distributed computers rather than simulated nodes.

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